# AUGMENTED REALITY BASED INDOOR NAVIGATION USING POINT CLOUD LOCALIZATION

By

Vishva Patel

A thesis submitted in partial fulfillment of the requirements for the degree of Master of Science (MSc) in Computational Sciences

The Faculty of Graduate Studies

Laurentian University

Sudbury, Ontario, Canada

**THESIS DEFENCE COMMITTEE/COMITÉ DE SOUTENANCE DE THÈSE**
**Laurentian Université/Université Laurentienne**
Faculty of Graduate Studies/Faculté des études supérieures

| | |
|---|---|
| Title of Thesis<br>Titre de la thèse | AUGMENTED REALITY BASED INDOOR NAVIGATION USING POINT CLOUD LOCALIZATION |
| Name of Candidate<br>Nom du candidat | Patel, Vishva |
| Degree<br>Diplôme | Master of Science |
| Department/Program<br>Département/Programme | Computational Sciences |
| Date of Defence<br>Date de la soutenance | June 24, 2021 |

**APPROVED/APPROUVÉ**

Thesis Examiners/Examinateurs de thèse:

Dr. Ratvinder Grewal
(Supervisor/Directeur(trice) de thèse)

Dr. Ramesh Subramanian
(Committee member/Membre du comité)

Dr. Kalpdrum Passi
(Committee member/Membre du comité)

Dr. Nirbhay Chaubey
(External Examiner/Examinateur externe)

Approved for the Office of Graduate Studies
Approuvé pour le Bureau des études supérieures
Tammy Eger, PhD
Vice-President Research (Office of Graduate Studies)
Vice-rectrice à la recherche (Bureau des études supérieures)
Laurentian University / Université Laurentienne

**ACCESSIBILITY CLAUSE AND PERMISSION TO USE**

# Acknowledgements

I would like to express my deepest gratitude and appreciation to my supervisor, Dr. Ratvinder Grewal, who gave me the opportunity and possible support to make this research successful. I believe I have got the finest supervisor who has been standing with me throughout the educational journey. He was always available to clear all my doubts and handle all the queries with patience. I am also thankful to Professor Dean Millar and Dr. K. Passi for their help during my studies and the CHILL-weekly research group for their assistance with the research.

I want to thank my technical coordinator, Nikhil and Baran Korkmaz, for providing all the server requirements for the training phase. They were always available and supported all the dependencies required in the environments.

I also want to thank my parents, brother, and friends who encouraged me and helped me fulfil my dreams. I want to give a shout-out to all my participants for their help and support for the testing phase.

Finally, and most significantly, I offer special thanks to my parents for their support and patience, believing in me, and trusting my calibre.

# Abstract

People of various ages may find it difficult to navigate complex building structures as they become more prevalent. The future belongs to a world that is artificially facilitated, and Augmented Reality will play a significant role in that future. The concept of Indoor Navigation using a smartphone-based Augmented Reality technology is explored in this research. Using readily available and affordable tools, this study proposes a solution to this issue. We built an Augmented Reality-based framework to assist users in navigating a building using ARWAY, a software development toolkit. To find the shortest paths, we used the Point Cloud Localization and A* pathfinding algorithms. A shop inside a shopping centre, a particular room in a hotel, and other locations can be easily located using this app, and the user is given fairly precise visual assistance through their smartphone to get to his desired spot. The proposed framework is based on augmented reality, and point clouds are the most important components. The application allows the user to choose their desired destination as well as change their destination at any time. To find the results from the technical, subjective, and demographic responses, we used hypothesis testing and validation with statistical analysis and exploratory data analysis methods.

**Keywords**: Augmented Reality (AR), Virtual Reality (VR), ARWAY, Point Clouds, A*

# Table of Contents

Acknowledgements ..... 2

Abstract ..... 3

List of figures ..... 6

List of tables ..... 7

Chapter 1 ..... 8

Introduction ..... 8

1.1 Background ..... 8

1.2 Existing Methods ..... 11

1.3 Objective ..... 12

1.4 Outline of the thesis ..... 14

Chapter 2 ..... 15

Literature Survey ..... 15

2.1 Types of Indoor Positioning Methods ..... 15

2.1.1 Radio Frequency (RF) ..... 15

2.1.2 Wi-Fi Access Points ..... 16

2.1.3 Bluetooth ..... 17

2.1.4 Optical wireless positioning ..... 18

2.1.5 Computer vision ..... 19

2.1.6 Discrete positioning with computer vision ..... 19

2.1.7 Continuous positioning with computer vision ..... 20

2.2 Literature Review on Point Cloud Localization as a method for Indoor Positioning used in this study ..... 23

2.3 Literature Review on Alternate Indoor Positioning methods ..... 27

Chapter 3 ..... 30

UI Design ..... 31

3.1 AR based indoor navigation application ..... 31

3.1.1 Algorithm A* ..... 31

3.1.2 User localization ..... 32

3.2 Application Methodology with User Interface ..... 36

Chapter 4 ..... 42

Methodology ..... 42

4.1 Objective ..... 42

4.2 Hypothesis ..... 43

4.3 Approach and Validation ..... 43

4.4 Questionaries’ design ........ 44
4.5 Participant recruitment ........ 46
4.6 Steps to perform task with 2D Map ........ 47
4.7 Steps to perform experiment with mobile based AR application ........ 47
4.8 Selected Paths ........ 47
Chapter 5 ........ 49
Results and Analysis ........ 49
5.1 Mobile based AR Application Navigation ........ 56
5.2 2D Physical Map based Navigation ........ 59
5.3 Demographic Questionnaire ........ 62
5.4 Statistical Analysis ........ 64
Chapter 6 ........ 68
Conclusions ........ 68
6.1 Limitations and Future Work ........ 69
6.2 Final Thoughts ........ 70
References ........ 71

# List of figures

Figure 1 Navigation in Augmented Reality ........................................................................................ 10
Figure 2 Point cloud map of 6th floor……………………………………………………………………………………….35
Figure 3 Developer Portal: ARWAY……………………………………………………………………………………………36
Figure 4 Experimental Map………………………………………………………………………………………………………. 36
Figure 5 Initialization of Application……………………………………………………………………………………….37
Figure 6 Mapping Mode……………………………………………………………………………………………………………37
Figure 7 Navigational Options available to users after Mapping Mode……………………………………….37
Figure 8 Questionaries' design……………………………………………………………………………………………………41
Figure 9 Detail of user guidance evaluation on each path for AR based Indoor Navigation………………48
Figure10 Physical Map of the floor…………………………………………………………………………………………….48
Figure 11 User Experiments for 2D Physical Map based Indoor Navigation ...................................... 50
Figure 12 Comparison of Time Taken for each path while using AR application and 2D physical Map ......................................................................................................................................... 51
Figure 13 Comparison of Time taken on a bar-graph………………………………………………………………….51
Figure 14 Time Differences for Each User (2D Map Navigation - AR Navigation)………. ....................... 52
Figure 15 Descriptive statistics of AR app and 2D map ...................................................................... 52
Figure 16 Technical Question 1 responses (1-7) - AR based Navigation............................................. 53
Figure 17 Technical Question 3 responses (1-7) - AR based Navigation............................................. 53
Figure 18 Technical Question 4 responses (1-7) - AR based Navigation............................................. 54
Figure 19 Technical Question 5 responses (1-7) - AR based Navigation............................................. 54
Figure 20 Technical Question 6 responses (1-7) - AR based Navigation............................................. 55
Figure 21 Technical Question 7 responses (1-7) - AR based Navigation............................................. 55
Figure 22 Technical Question 1 responses (1-7) - 2D Physical Map based Navigation ....................... 56
Figure 23 Technical Question 2 responses (1-7) - 2D Physical Map based Navigation ....................... 57
Figure 24 Technical Question 3 responses (1-7) - 2D Physical Map based Navigation ....................... 57
Figure 25 Technical Question 4 responses (1-7) - 2D Physical Map based Navigation ....................... 58
Figure 26 Technical Question 5 responses (1-7) - 2D Physical Map based Navigation ....................... 58
Figure 27 Age of Participants .............................................................................................................. 59
Figure 28 Gender of Participants ......................................................................................................... 59
Figure 29 Education Level of Participants……………………. ................................................................... 60
Figure 30 whether the user used Indoor Navigation before or not ..................................................... 60
Figure 31 whether the user used 2D Maps before or not……………………………………………………………….60
Figure 32 whether the user used google Map's AR before or not……………………………………………….60
Figure 33 whether the user used AR headset before or no……………………………………………………………60
Figure 34 QQ-plot - Normality Check……………………………………………………………………………………….62

# List of tables

Table 1 Advantages and Disadvantages of Indoor Positioning techniques ........................................ 22
Table 2 Comparison of common position systems used for localization ........................................... 23
Table 3 Selected Paths ........................................................................................................ 48
Table 4 Detail of user guidance evaluation on each path for AR based Indoor Navigation ................ 50
Table 5 User Experiments for 2D Physical Map based Indoor Navigation ......................................... 52
Table 6 Average Response (1-7) for AR based navigation Questionnaire .......................................... 58
Table 7 Average Response (1-7) for 2D Map based navigation Questionnaire ................................... 62

# Chapter 1

# Introduction

Some people, at some point in their life, may get lost inside a large auditorium, struggled to find their exit point at the airport, or may get late to a lecture because they couldn't find the right lecture hall (Ajith et al, 2020). But this way of getting lost could soon be a thing of the past in complex and large venues. Applications for indoor navigation for mobile devices are now popular and people need them to locate destinations within large buildings and many other places, institutions. Several indoor navigation applications use multiple techniques, such as Wi-Fi Fingerprinting and Bluetooth to make this possible. In order to direct the users to their destinations, these applications use pre-calculated paths and set context maps. Users of these devices need to provide an understanding of how indoor maps and general map reading signals operate directly. These devices will need to run complicated and precise measurements to evaluate the route directions before the navigation begins, which may be influenced by unreliable Wi-Fi signals. In this thesis, we introduce an indoor mapping that is expanded with Virtual Reality to 3D features, with an increasing interest for trade and general wayfinding.

## 1.1 Background

The advancement of indoor positioning and navigation systems and solutions is a hot subject, owing to its role in future industrial approaches, among other things. Large companies have numerous advanced systems for indoor localization in most of their planned technology, architectural designs, and patterns, besides those that have already upgraded their applications, or an application programme interface (API, which is a series of routines, protocols, and resources for building software applications), according to the research on this subject.

The innovative indoor navigation is Indoor venue and spatial data visualization definition on a 2-Dimensional or 3-Dimensional optical map. It helps us to navigate through universities, large malls, hospitals, the auditoriums and so on. Indoor navigation is very complicated in terms of difficulty. Compared with outdoor navigation, it is distinct. In the instance of millions of people already use outdoor navigation, technology such as GPS is available, as it takes a great deal of performance. Built-in GPS and maps are presently found in Smartphones and advanced smartwatches.

In outdoor settings, navigation systems are commonly used, but indoor navigation systems are still in the early stages of growth. GPS, Bluetooth, Wi-Fi, RFID and Sensor Chip technologies make use of the latest available devices. The technology for Bluetooth is affordable but has limited range and accuracy. We need to set up Bluetooth hotspots in the building for efficient position monitoring and navigation using this technology. For other technologies, such as Wi-Fi, RFID and Sensor chips, the same applies. The expense of installation and repair is outrageously high with all these tools, and a shift in weather conditions will affect the signal intensity of the hotspot if one system breaks down.

Existing infrastructural services are inevitable for the perfect operation of all of these current structures. In this study, by implementing an augmented reality-based indoor navigation technology to help people navigate in indoor environments, we put forward a relatively inexpensive, reliable and efficient approach to achieve the same objective.

Usually, an augmented reality navigation system work in the following way:

1. Obtain the real-world experience from the viewpoint of the consumer.

2. Obtain location data for user monitoring. The GPS coordinates are usually this information.

3. Generate knowledge about the virtual world based on the real-world view and information about the venue.

4. Register the visual knowledge created with the real-world view and present the information to the user, thus providing an augmented reality.

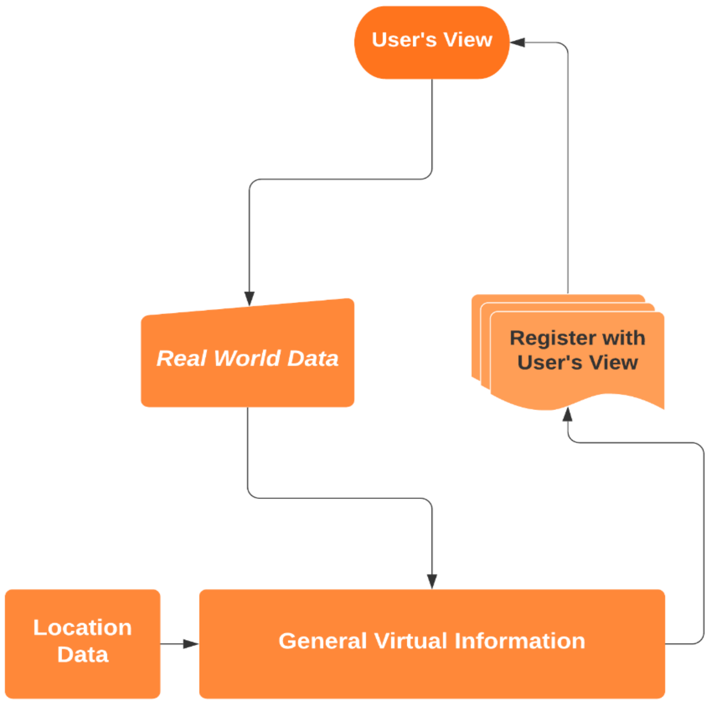



*Figure 1. Navigation in Augmented Reality*

Applications of Augmented Reality (AR) allow a user to communicate on top of a physical world with digital entities (Azuma et.al, 1997), often connecting real objects to digital content. This method of linking involves understanding an environment's semantics, a job that proves to be challenging. The localization of digital twins is one solution to this problem. If the precise position in the world of the computer is known, then a digital twin will provide the environment with semantics. Localization or pose prediction is called determination of this spot.

Although systems such as GPS in outdoor environments are able to provide a georeferenced location, they are vulnerable to errors in indoor environments, rendering them unusable for many applications as localization. Indoor localization should also be seen as a distinct concern from outdoor localization.

## 1.2 Existing Methods

There are two existing indoor mapping solutions, which are Bluetooth Beacons-based indoor mapping and RSSI-based Wi-Fi Fingerprinting indoor mapping. The Bluetooth Beacons are transmitters for hardware (Satan et.al. 2018). They are low energy Bluetooth systems that broadcast their identifier to neighbouring portable electronic devices. When they are close to the beacons, the hardware in these beacons enables laptops, smartphones, and other gadgets to perform acts. Bluetooth Beacons use Bluetooth low energy proximity sensing to relay a globally specific identifier.

A compliant program or an operating system then takes up these identifiers. Several bytes are also sent along with identifiers that can be used to decide the physical location of the device, monitor clients, or can also activate a location-based device behaviour, such as a social media check-in or a route warning. Another current method is Wi-Fi Fingerprinting using RSSI. The acronym for Obtained Signal Intensity Indicator is RSSI (Chabbar and Chami et.al. 2017).

They are generally invisible to the naked eyes. Using RSSI, the power present inside the received radio signal may be determined. Standard printing of fingers is also based on RSSI, although there is a minor distinction. In conventional fingerprinting, there are many access points and it was clearly focused on capturing the signal intensity from these access points, which are in range. This information is then stored in a database along with the known coordinates of the client computer in an offline process. This knowledge that is preserved can be probabilistic or deterministic.

For the distribution and implementation of Wi-Fi routers and Bluetooth beacons in the indoor environment. Some application systems often have high latency during the detection process, such as Bluetooth and infrared approaches. Since these Systems used for indoor positioning can be usually divided into two categories, wireless communication methods and computer vision methods. Technologies such as Ultra-wide Band (UWB), Wireless Local Area Networks (WLAN), and Radio Frequency Identification (RFID) are used in wireless communication methods to localize a unit.

These technologies also require physical infrastructures, such as technologies that are common solutions for localization, have difficulty estimating the direction of the user, and are thus not suitable for AR applications. In contrast, machine vision methods are more suited for AR-based applications, and recent tests have shown computer vision solutions to be more reliable in addition to Wi-Fi based fingerprinting. A widely studied indoor positioning solution focused on vision includes picture recognition from live camera feed of the real world.

## 1.3 Objective

This research is about proposing a methodology for navigating an indoor area in student living apartments using an augmented reality (AR) application. For this research, the software is designed, which is using cloud based Augmented Reality Tool Kit and SDK based on the real-world view direction to quickly get the desired location around student living at 50 Lisgar street. For conducting experiments, there were two different experimental tasks that we used to navigate the experiment building using a 2D map of the location. Another is the main prototype, augmented reality (AR) indoor navigation using point cloud map localization technique to locate users in the building. To achieve this goal based on the two created tasks, we conducted an analysis. Both tasks are represented by two different types of navigation around the apartment living building. In the experiment, we want to check how the participants will get to their desired destination using an AR prototype. After the experiment, to consider participants' safety during this covid-19 pandemic time, they were needed to fill out a seven-point Likert scale questionnaire form through the listed menu option in the given application to know the feedback for the prototype. And for data collection and analysis, this study compared the timing of each participant's results; they took to complete the given task.

Participants were recruited using a random selection method through social media or by contacting them through email and phone calls. Three groups of 24 participants were selected for this experiment. Using the random number generation table, the researcher assigned 10-10 people to two experimental groups and the remaining four people to the control group. Any interested people who are currently living to the apartment building can participate in this study. Questionnaire method is used to allow the respondents to express how much they agree or disagree with using this application.

The framework is developed using cross-platform ARWAY (https://arway.app/) which can help us build hyper-accurate indoor positioning apps through Augmented Reality Cloud which can enable residents during their stay period at student living apartment to locate directions to common room, laundry room, cleaning supply room and in case of emergency exit (Fire exit) using augmented reality. This will allow tenants to navigate in unknown interior locations and arrive at their destination using the most effective approach possible. We used a 2d map of the floor and an augmented reality application for the experiment. ARWAY is used because of its efficiency, ease to use, scalability which removes the hardware dependency and leverages mobile cameras to safely interpret and navigate the GPS-denied locations in indoors.

ARWAY uses the Mapping Engine, which captures unique 'feature points' in each camera keyframe and then by matching those features continuously in each frame, it can estimate the camera position in real-time. These matched feature points are converted into a point cloud map that is stored in cloud infrastructure. During '**localization'**, when a device needs its localized Pose for Augmented Reality, their Software Development Kit allows developers to request localization data from previously-stored 3D maps.

In this study, we create AR based indoor navigation application using ARWAY (a software development toolkit), which is used because of its efficiency, ease to use, scalability which removes the hardware dependency and leverages mobile cameras to safely interpret and navigate the GPS denied locations in indoors. ARWAY has not been reported any published research study (other than blog posts) similar to this study since it founded on august 2018. By using ARWAY to develop real-time indoor navigation application and comparing that with 2d mode of navigation; we conducted a study to determine which navigation method would work better to reach the destination in a lesser time.

## 1.4 Outline of the thesis

The rest of the thesis is organized as below:

In Chapter 2, we discussed literature review of related works towards Indoor Positioning using Augmented Reality.

In Chapter 3, the terminologies, UI design in detail.

In Chapter 4, we discussed the methodology. Hypothesis validation, experiments and subjective and technical analysis details with the participants who used the application.

In Chapter 5, we discussed the results of our experimentation.

Finally, Chapter 6 concludes the study and future work is discussed.

# Chapter 2

# Literature Survey

When compared to the outdoor positioning, indoor positioning faces multiple problems and has specific requirement. Satellite signals such as GPS are more difficult to track in indoors because radio frequency signals are attenuated by barriers such as walls in a building. In comparison, indoor positioning is commonly associated with more specific locations than outdoor positioning (Mautz, 2009). For e.g., GPS has an accuracy of 10-20 metres measured as a root mean square error (Dardari et al., 2015), and on the other hand some indoor positioning systems can achieve accuracies of few centimetres only. In addition, indoor positioning systems besides the planar location, are usually involved in the user's altitude which indicates both discrete details such as the floor of the building, as well as the exact height of the unit from the actual floor of the user. If consumer mobile devices are used for indoor real-time positioning systems, then the positioning algorithm's efficiency, speed, accuracy, and computational load play a crucial role in the system's functionality and flexibility.

## 2.1 Types of Indoor Positioning Methods

Broadly, there are various methods developed by the researchers as methods for indoor positioning which have been discussed in this chapter.

### 2.1.1 Radio Frequency (RF)

Cellular towers and WI-FI are used today by mobile positioning systems to help position GPS which is also known as assisted GPS or AGPS (Filonenko et al., 2013). When compared to using GPS alone, this method increases the precision and efficiency of indoor positioning, but it is still inadequate for realistic indoor positioning use. As reference points, Wi-Fi connection points or Bluetooth beacons may be used. Indoor positioning accuracy based on RF signal intensity is usually in the range of a few metres.

The radio frequency based indoor positioning system under consideration in this research are Wi-Fi and Bluetooth/BLE which are discussed in detail below along with advantages and disadvantages.

### 2.1.2 Wi-Fi Access Points

The use of WIFI access points as reference points for indoor positioning has the significant advantage of having no extra equipment. For connectivity as well as localization, the access points may be used simultaneously. Bielsa et al. (2018) examined how well an indoor positioning system can work where publicly accessible WIFI access points are used without changing their standard communication protocols in which 60 GHz range millimetre waves were used in an office setting with a combination of human traffic. Related meter-level accuracies can be accomplished with commercial WIFI infrastructures, according to other studies. Martin et al. (2010) reached an accuracy of 1.5 metres using fingerprinting, thus showing that both the offline and the online process can be carried out with a smartphone. Husen and Lee (2014) reached an accuracy of 1.8 metres, while still recording the incredibly rugged orientation of the user (one of four main facing directions).

**Advantages:**

There are various advantages of Wi-Fi Indoor Positioning which are listed below.

- It provides high positioning accuracy, especially in over-crowded places
- Fast speed

- Surrounding WIFI can be positioned even if it is not connected.

**Disadvantages:**

There are various disadvantages of Wi-Fi Indoor Positioning which are listed below.

- WIFI dependency – It cannot be located without opening WIFI
- It is must be in a networked state.

### 2.1.3 Bluetooth

Bluetooth Beacons that transmit signals are lightweight, battery-powered devices that broadcast Bluetooth signals. This signal can carry information which includes the ID, its calibrated strength at a known distance, and a URL or an arbitrary string connection, depending on the protocol. A beacon can be left unattached to something in a location, or connected either by screws or by using the sticker of the unit. If required, a beacon may be placed upside down on a ceiling or concealed from view. Subedi and Pyun (2017) suggested a fingerprinting indoor positioning device based on BLE beacons. Additionally, the authors used a technique in the method called Weighted Centroid Localization (WCL) which is equivalent to multilateration. The authors were able to minimise the required number of deployed BLE beacons by eliminating noisy RSS values and using both fingerprinting and Weighted Centroid Localization approaches at the same time to achieve the same degree of precision compared to the case where only fingerprinting was used. Furthermore, the offline process needs less effort for this hybrid strategy. This machine was able to obtain an accuracy of 1–2 metres in a hallway and an office room, where the BLE beacons were fitted to the ceiling, tests were carried out.

**Advantages:**

There are various advantages of Bluetooth based Indoor-Positioning which are listed below.

- It is cost-effective, unobtrusive hardware

- It has low energy consumption
- It is flexible integration into the existing infrastructure (battery-powered or power supply via lamps and the domestic electrical system)
- It works where other positioning techniques do not have a signal
- It is compatible with iOS and Android
- It has high accuracy compared to Wi-Fi (up to 1m)

**Disadvantages:**

There are various disadvantages of Bluetooth based Indoor-Positioning which are listed below.

- It costs additional hardware
- An application is required for client-based solutions
- It has relatively small range (up to 30m)

### 2.1.4 Optical wireless positioning

Optical wireless communication (or optical free-space communication) is a series of techniques for exchanging data wirelessly using infrared or visible light. Visual Light Communication (VLC) is a subset of wireless optical communication in which data is conveyed through visible light. Visible light has larger frequencies than radio waves and higher bitrates can theoretically be obtained. Because of the ubiquity of indoor light sources and because optical light does not suffer as badly from interference as radio waves, VLC is an enticing solution to Wi-Fi data sharing in the future and an active field of study. (2017, Kaushal et al.)

**Advantages:**

Optical Wireless Indoor Positioning has a number of benefits, which are described below.

- In general, an optical and vision-based positioning system makes use of a mobile device's sensor and computing power. Inertial sensors, such as accelerometers, gyroscopes, and magnetometers, are integrated into modern electronic devices. As a result, infrastructure installation is reduced (Möller et al., 2012).
- Furthermore, as opposed to other positioning systems, this system is considerably less expensive (Mulloni et al., 2011).

**Disadvantages:**

Optical Wireless Indoor Positioning has a number of drawbacks, which are described below.

- The device has a poor level of precision.
- The device is subjected to interference from a variety of sources, including bright light and motion blur, as well as major accumulative errors that can result in bad results (Klopschitz et al., 2010; Möller et al., 2012).
- Since a server saves location information for monitoring and navigation purposes, privacy issues can arise in certain situations.

### 2.1.5 Computer vision

Rosenfeld (1988) defines computer vision (CV) as a set of techniques that infer information about a scene by analysing images of that scene. A computer vision algorithm takes a 2D image as an input and produces a description as an output. Often, the goal of this process is to recognize objects from the image. Rosenfeld (1988) describes the general process of 2D object recognition as follows. The process of detecting specific parts of an image is known as segmentation, or feature recognition.

### 2.1.6 Discrete positioning with computer vision

Mulloni et al. (2009) illustrated how to use mobile cameras for indoor positioning in a conference guide implementation in 2009. The authors attached rectangle-shaped contractual markers to signposts in the conference grounds (similar in purpose and appearance to QR codes). Every marker had a specific visual ID associated with the signpost's position. The application was able to determine the 3D location and direction of the user with regard to the markers in real time with centimetre-level precision. The user had to point the camera directly at the marker, and they had to be close enough to the signpost so that the marker was visible to the came in necessary detail.

However, given a marker's known real-world scale and how perspective projects it onto a 2D image, the camera's relative direction and orientation to the marker can be easily determined using linear algebra (Fusco and Coughlan, 2018). However, the output knowledge from this method is discrete in the sense that it defines which signpost the consumer is looking at. This technique cannot place the viewer if there are no markers in the camera's vision. As a consequence, the question is whether machine vision can offer continuous indoor navigation.

### 2.1.7 Continuous positioning with computer vision

Fusco and Coughlan (2018) created an indoor visual positioning system utilising this approach to support visually disabled individuals (the system could position the mobile device, but not yet navigate it). Visual-inertial odometry (VIO) was used by their device to place the user in between visual signs. With regard to the environment, augmented reality technologies will place the mobile device locally with a high update rate.

Indoor Positioning is also possible without impromptu visual markings. A typical computer vision technique for scene recognition is to catch and use 3D point clouds. A camera takes photographs of a 3D scene in normal or regular conditions in a passive point cloud acquisition process. A computer vision algorithm is able to capture a range of 3D positions on the surfaces of objects in the picture, either by providing several views or by rotating the camera in the scene (structure from motion), and the current camera poses in reference to these locations. It is possible to recreate the geometry of the inner space in such a way. If the same indoor space has been scanned before, the newly scanned and previously scanned point clouds can be matched to approximate the latest camera pose in real-world indoor coordinates. In addition to the location, the orientation of the client computer can be calculated. (2016 Weinmann)

Using computer vision, a number of techniques for localization and navigation have been developed. Simultaneous Localization and Mapping is a common technique for autonomous vehicles that originated from the robotics community (2015, Gerstweiler, Vonach and H. Kaufmann). The Simultaneous Localization and Mapping method aims to gather spatial data from the atmosphere such as Signal Intensity and 3D Point Clouds in order to create a global reference map when monitoring the subject's location (2006, Bailey and Whyte). Simultaneous Localization and Mapping algorithms are used in a range of applications, including Wi-Fi, Bluetooth, feature detection, and image recognition (2015, Gerstweiler, Vonach and H. Kaufmann). For Simultaneous Localization and Mapping, either of these data types may be used.

Any of the innovations mentioned above has its own set of advantages and disadvantages. 2D positioning systems (GPS, beacons, ceiling antennas) are successful, but they have a long latency, poor accuracy, and no height detail. It's difficult to scale markers and visual recognition, and it necessitates user interaction

Table 1 shows the comparison of advantages and dis-advantages of Indoor Positioning techniques.

*Table 1 Advantages and Disadvantages of Indoor Positioning techniques*

| Indoor Positioning Method | Advantages | Disadvantages |
|---|---|---|
| **RF based WIFI Access Points** | • High positioning accuracy.<br>• Faster.<br>• Surrounding WIFI can be positioned even if it is not connected. | • Not functional without WIFI connectivity.<br>• Must be in a networked state.<br>• Vast change of signal over a small distance |
| **RF based Bluetooth Beacons** | • Cost Effective.<br>• Low energy consumption.<br>• Flexible integration.<br>• No signal or connectivity required, just Bluetooth devices.<br>• Good compatibility with devices. | • Additional hardware cost.<br>• Need Application Management system or client-based solution.<br>• Smaller range. |
| **Optical Wireless Positioning** | • Not much infrastructure is required, as it utilizes the user's smartphone processing power and sensors.<br>• Less Expensive. | • May result in poor precision.<br>• Privacy issues with the users as the information is stored in the server.<br>• Affected by dull light, bright light and motion blur etc. which causes error resulting in poor precision. |
| **Computer Vision** | • Not much Expensive.<br>• Higher Accuracy<br>• No Accumulative errors. | • Installation of infrastructure is not easy.<br>• Requires mapping. |

Table 2 below shows the comparison of some of the methods based on type, accuracy, setup, cost and usability.

*Table 2 Comparison of common position systems used for localization*

| Name | Type | Accuracy | Setup (1=easy, 5=hard) | Costs | Usability |
|---|---|---|---|---|---|
| **Bluetooth Beacons** | 2D | 3-8m | 3 | Low | High |
| **Compass based** | 2D | 5-10m | 4 | Medium | Medium |
| **Ceiling Antennas** | 2D | 10-50cm | 5 | High | High |
| **GPS** | 2D | 5-15m | 1 | Low | Medium |
| **Visual Recognition / SLAM** | 3D/ 6DoF | 10-30cm | 4 | Medium | Low |
| **Markers / QR codes** | 3D/ 6DoF | 5-15cm | 1 | Low | Medium |

## 2.2 Literature Review on Point Cloud Localization as a method for Indoor Positioning used in this study

In the last several years, various reviews on as-built modelling from point clouds have been released (Volk, Stengel and Schultmann et.al. 2014) (Patraucean, Armeni, Nahangi, Yeung, Brilakis and Haas et.al. 2015) (Liu and Zlatanova et.al. 2013). The majority of the works focused on the effective reconstruction of structural building components (Oesau, Lafarge and Alliez et.al. 2014) (Mura, Mattausch and Pajarola et.al 2016) (Tran, H.; Khoshelham, Kealy and Díaz-Vilariño et.al. 2019) and openings, while the correct modelling of floor elements, the modelling of free space, and the modelling of obstacles received less consideration, considering their significance for indoor path finding.

Several recent works have discussed the thorough simulation of floor components. In indoor conditions, point clouds and handheld laser scanner trajectories were combined to segment and identify floors into stairwells, stairs, and flat surfaces (Staats, Diakité, Voûte, and Zlatanova et.al. 2017) (Balado, Vilariño, Arias, and González-Jorge et.al. 2018). The process begins with a projection in the point cloud discretized into a voxel-based model and an area rising, which is then accompanied by a projection in the point cloud discretized into a voxel-based model. Outdoors, the trajectory direction was used to identify road regions and, as a result, define ground components into curbs, sidewalks, ramps, and stairs based on geometrical and topological features (Balado, Vilariño, Arias and Soilán et.al. 2017) (Vilariño, Verbree, Zlatanova and Diakité et.al. 2017).

In terms of modelling the free space, trajectory is a valuable source of knowledge. It's fair to say the trajectory represents the system's direction during the integration phase. This is the advantage in indoor modelling to detect open doors, which function as transition elements between two adjacent spaces (Vilariño, Verbree, Zlatanova and Diakité et.al. 2017). After detecting the existence of a door, the timestamp correspondence between the trajectory and the point cloud was used to subdivide the raw point cloud into linked rooms using an energy-minimization feature in Comparison (Vilariño, Verbree, Zlatanova and Diakité et.al. 2017). Following that, the subdivided spaces were subjected to a surface-based simulation approach. Reference (Nikoohemat, Peter, Elberink, Vosselman, et.al. 2018) used trajectory to mark doors, floors, and walls and ceilings in indoor spaces. Nikoohemat, Peter, Elberink and Vosselman (2018) built on this work by introducing morphological operations and related components to subdivide the indoor space recently proposed a technique for extracting topological relationships between the spaces of a 3D indoor system modelled from point clouds in terms of indoor navigation. Obstacles were not taken into account, considering the fact that these studies solved the simulation of indoor systems and the extraction of topological interactions between them with considerable results.

Despite the fact that the Guzzi and Di Carlo (2016) provides another intriguing analysis in which indoor geographic information system (GIS) maps were used to construct a topological mapping graph for wheelchair users to prepare their routes. Also, challenges were not taken into consideration in this article. The bulk of previous research on obstacle-aware indoor navigation used 2D approaches.

De Berg, Van Kreveld and Overmars (2016) suggested a skeleton-abstraction algorithm that produces a graph of intervisible positions. Each node in the graph denotes a point position, and each edge denotes a visible connection between them. The idea took into account the existence of hazards as a series of 2D points, such as those found in CAD files or 2D floorplans. Goetz and Zipf (2014) also introduced a structured description of an indoor routing graph based on the 2D representation of indoor environments, in which the location of obstacles within rooms was manually defined in the indoor network by placing nodes around the obstacles. Wang, Zlatanova and Oosterom (2017) introduced a data model to assist vehicle pathfinding across moving obstacles in forest fires. The pathfinding took into account both static obstacles like trees and buildings.

The GIS-based simulation was put to the test in a case study in which the landscape, road network, trees, and buildings were all collected from OpenStreetMap, and the fire spread was defined by moving polygons crossing the network. Mortari et al. suggested a network-generation approach that takes challenges in indoor scenes into account. Obstacles were depicted as 2D geometry in the floor plane, and the process was based on predefined models. Since 2D floor plans were abstracted at various height ratios, the result was a 3D network. Xiong et al. suggested a framework for designing 3D indoor paths using semantic 3D models contained in LoD4 CityGML.

system takes obstacles into consideration; the method was checked on models that did not have any obstacles. Lui et al. (2018) invented a system for real-time indoor navigation based on grid models derived from 2D floor plans with predefined obstacles. Rodenberg et.al (2016) suggested an octree representation of indoor point clouds as a basis for indoor pathfinding. The A* pathfinding algorithm, which relies on heuristics to direct the search, was used to navigate through empty nodes, avoiding obstacles. Li et al. (2018) also recently presented a path-planning method for drones indoors based on occupancy voxel maps, and on which the navigable space was composed of the empty voxels.

The study done by Ajith et al. (2020) is Indoor Mapping Based on Augmented Reality Using Unity Engine, where the researchers implemented an indoor navigation app for both android and iOS using a place note SDK. However, there is no software available at the time of publishing where we can access the software code. So, by implementing an AR indoor navigation application using the ARWAY software development toolkit, we conducted a comparative study of 2D physical map and AR applications to determine which navigation method would navigate indoor in less time.

We used Point cloud Localization with A* pathfinding algorithm because of the following reasons.

1. Scalability: It is highly scalable.
2. Reliability: It provides high reliability and efficacy.
3. Accurate: It is able to accurately guide a user to its destination.
4. Easy-to-deploy: It does not require any indoor map or dedicated indoor localization system deployment initially.
5. Infrastructure-free: It is independent of any infrastructure, such as Wi-Fi access point, Bluetooth beacons etc which is usually unnecessary for indoor environment to offer such infrastructures.
6. Robust: It is robust to environment variations and crowds and also able to detect deviation events to notify the users.

7. Universal: It is able to guide a user to any destination from its current location, rather than from a few predefined locations.

Here is the reason why we use A* algorithm,

Nowadays, deducing position and route has become significant because it assists the user to get to the destination more quickly and easily. However, to reach the destination, knowing the only position is not sufficient because there are many rooms inside the building, such as hotels, universities, and malls. Thus, knowing the route to the destination is also very important to reach the destination in lesser time easily. The study was done by shiv et al. (2017), where they use the A* algorithm to find the shortest path to the destination. They also conducted a study to see why the A* algorithm is better than the Dijkstra algorithm. At the end of the study, they conclude that A* behaves much more similarly to Dijkstra's. The only difference between the algorithms is that A* gives a better path using a heuristic function while Dijkstra explores all possible paths. Therefore, a* accomplishes better performance by using heuristics to guide its search and gives the optimal result much faster. Based on the results of the study, we uses A* algorithm to find the shortest path to the destination.

## 2.3 Literature Review on Alternate Indoor Positioning methods

The optical and vision-based positioning system uses a mobile sensor or camera in a user's mobile device to assess the location of an individual or an object within a building by locating a marker or image that is within range (Mautz & Tilch, 2011; Klopschitz, Schall, Schmalstieg, & Reitmayr, 2010). A marker is a static target with markings that can be used as a reference within the field of view of an imaging sensor like a cell camera (Mautz, 2012). Barcodes, QR codes, and fiducials are only a few examples of identifiers. Marker-based and Augmented

Reality (Augmented Reality) are the two most popular methods for optical and vision-based positioning.

According to Chang, Tsai, Chang, and Wang (2007), Mulloni, Wagner, Schmalstieg, and Barakonyi (2009), and Raj, Tolety, and Immaculate (2009), a cell phone camera gets visual information using identifiers, such as QR codes (2013). A mobile computer with a monitor, a QR code, and a server make up the machine (Raj et al., 2013). The mobile device's camera is used to collect data by scanning the QR code's pattern, while the server is used for tracking and storing information including floor plan map data for retrieval as appropriate (Barberis et al., 2014; Chang et al., 2007; Mulloni et al., 2009).

While Chang et al. (2007) focused on monitoring people with neurological impairments in smart settings, Mulloni et al. (2009) focused on searching and reviewing real-time location details in an area to aid continuous navigation. To put it another way, Chang et al. (2007)'s research would not allow for real-time navigation like Mulloni et al. (2009)'s, but it can monitor users' movements over time. Scanning the QR code in the case of Raj et al. (2013) yields the floor map URL and geo-location information. As a consequence, the building's floor map is obtained and used for navigation (Raj et al., 2013).

However, in this situation, navigation is not real-time. In comparison to the previous positioning systems mentioned, the QR code's ease of use makes it a feasible indoor positioning system. It is simple to deploy, according to Chang et al. (2007), because of its low cost. Furthermore, user privacy is covered because certain implementations, such as Raj et.al. research do not include real-time positioning and alerts via a server (2013). Despite the fact that the mobile device is being monitored, the consumer location is not real-time in certain other solutions (Chang et al., 2007; Mulloni et al., 2009). The marker's location is decided by the user's position.

The markers are spread across the navigation area, and their location is determined by positioning the mobile device next to the marker (J. Kim & Jun, 2008). Real-time navigation is still possible with some other solutions, as shown by Barberis et. al. report's (2014). Furthermore, the system's accuracy is measured by the distance between the marker and the device, which is determined by the device's camera's resolution (Raj et al., 2013). If the camera resolution on the platform is insufficient, it may have a negative impact on the system's accuracy and performance (Ibid.).

Barberis et al. (2014), on the other hand, may not need knowledge of the device's camera's resolution or properties. However, because of the extra infrastructures, these networks become more complicated and costly. As a result of these problems, the AR approach was established as an alternative.

Augmented Reality (AR), like marker-based approaches, uses a handheld system with a camera, a marker, and a server (Raj et al., 2013). The data is captured by scanning the pattern of the marker with the mobile device's sensor, while the server is used for location estimation, position determination, and real-time monitoring and navigation (Chang et al., 2007; Mulloni et al., 2009). AR (Möller, Kranz, Huitl, Diewald, & Roalter, 2012) is the overlay of simulated objects with the physical world using visual markers or photographs for orientation, tracking, and navigation.

Klopschitz et al. (2010), Mulloni, Seichter, and Schmalstieg (2011), and Möller et al. (2012) propose that AR obtains visual knowledge by smoothly overlaying a user's vision with position information connected to an image store in a centralised location or server. Optical marker identification, image sequence matching, position recognition, and location annotation are all performed by the server (Klopschitz et al., 2010; J. Kim & Jun, 2008). According to Mautz and Tilch (2011), the server sends the recognised location data to the mobile user, allowing for real-time positioning and navigation. Mulloni et al. (2011) and Möller et al. (2012) based their research on improving efficiency focused on the interface of an AR indoor navigation system so that navigation in indoor environments can be made better.

While navigating, users are guided by activity-based guidance and information points such as markers positioned in the area to assist accurate positioning and efficiency. As a consequence, navigation errors are greatly minimised. Robustness, simplicity, and accessibility are considerations that are taken into account during the deployment process to accomplish this (Möller et al., 2012; Mulloni et al., 2011). While most positioning and navigation systems use a marker-based approach, Klopschitz et al. (2010) use a new “markerless-based” approach in their research. For matching and monitoring purposes, this method makes use of existing image features.

Since matching image features in real time can be difficult, the markerless approach makes certain assumptions about the mobile device's sensor (Klopschitz et al., 2010). Furthermore, when more markers and a server are used, real-time positioning and navigation is accurate with AR (Möller et al., 2012). Despite the advantages of AR over marker-based systems, image matching can demand a large amount of computational power, raising the difficulty and affecting efficiency (Klopschitz et al., 2010). Furthermore, updating the server could result in an increase in both the cost and the cost of maintenance.

# Chapter 3

# UI Design

## 3.1 AR based indoor navigation application

The proposed indoor navigation APP's primary technology is the A* algorithm, which aids in deciding the shortest distance to the destination among the paths stored in the maps for various routes. Through walking and dropping way points on the road, we first save the routes to various destinations inside a $6^{th}$ floor lobby of apartment building. ARWAY SDK stores our guides, waypoints, and their positions in the cloud. The A* algorithm is used in a recursive loop to find the best possible route by comparing the distances between nodes starting at the beginning and ending at the end. The user's surroundings are first traced on a screen and then downloaded to the cloud (Azhar, Murtaza, Yousaf and Habib et.al. 2016). Many of the beginning and ending points are mapped first in this manner. The user learns his or her position inside a building by looking up the GPS coordinates of that location on the cloud during navigation, and then uses the map to navigate to the target location using way points (Wenge and Nan et.al. 2015).

### 3.1.1 Algorithm A*

The A* algorithm is a type of heuristic search algorithm that calculates the shortest path between two points by calculating the path's minimum cost. To evaluate which component to take, the assessment function is used.

This function can be denoted as

$$a(n) = b(n) + c(n)\ a(n)$$

where a(n) represents the evaluation function, b(n) shows with node n from staring point to destination. b(n) represents distance between two alternate nodes, which is fixed. c(n) represents the stretch between the initial and the final node, whose length we need to calculate in the most efficient way possible. For this we make use of Euclidean distance formula which is the square root of sum of squares of difference coordinates of the location points (Thomas and Sandor et.al. 2009). For example, points (a1, b1, c1) (a1, b1, c1) and (a2, b2, c2) (a2, b2, c2) in 3D space, the Euclidean distance between them is calculated as

$$\sqrt{((a2-a1)\ 2 + (b2-b1)\ 2 + (c2-c1)\ 2)}$$

### 3.1.2 User localization

In order to find indoor localization, we need to identify the area of the building where the user is situated using the smartphone's camera based on the user's position. To process and align the image stored in our cloud storage, we use computer vision. When the smartphone detects an object in the environment, it displays green dots on the screen. We begin by mapping the surroundings of all the objects in the region and storing it in a cloud database. When a user requests a route to a location within the building from his current location, he must first search the area surrounding him in order for the device to recognize his location and then indicate the fastest path to his destination. We suggest an indoor navigation application in this study.

With the aid of directional 3-D markers integrated with their phone's GPS location, this software enables users to quickly navigate around complicated buildings such as hospitals. We use the A* algorithm to find the most cost-effective (precise) path to our destination by plotting it first and then using computer vision to localise it later (He, Wang and Cao et.al. 2012). We use the ARWAY SDK, which is an AR-based SDK that provides a cloud storage solution for storing the position of each way point in a map for an unlimited number of maps and making data access simple. Each of the way points' coordinates is saved separately, and a script can be used to access them as needed.

We need to map all possible paths to the final destination from a starting point that the user can select, as well as all other routes from one point to another within the 6th floor lobby of apartment building, before we can load the maps. We accomplish this by using the smartphone to map the route using waypoints, which are basically 3D markers that aid in the marking of a specific path. We also use the smartphone's gyroscope for this, which can later be used to guide the 3D directional arrows on the screen to lead the end user to his destination. ARWAY SDK automates the process and assigns a specific location for each of the nodes, storing 3D waypoints as separate nodes with their location coordinates on cloud servers. The software uses the A* algorithm, which allows it to quickly determine the shortest path to the appropriate destination by comparing the position coordinates of all the way points stored in the cloud (He, Wang and Cao et.al. 2012).

The use of point cloud localization and the A* algorithm for shortest pathfinding is proposed in this study. To collect initial navigational information, point clouds are first used to recreate semantically rich 3D models of building structural components. Potential obstacles to navigation are classified in the point cloud and directly used to correct the path according to the mobility skills of different users. Participants derived enjoyment or learnt new ways of navigating indoor areas using this application. It also helped the users learn new ways to navigate unknown indoor areas to find their destinations without asking other people for directions. The other objective of developing an application for the indoor area of student living apartment si to provide a real-world view direction to the users. Furthermore, it can add a point of interest view on the application to get more details about each room number and details about common rooms, laundry room etc. The starting point is a categorised point cloud, in which ground components such as roads, pathways, crosswalks, curbs, and stairs have been previously classified. The obstacle class is made up of the majority of the points. Individualizing and optimising ground elements into representative points, which are then used as nodes in the graph development, is the first stage in the technique. To fine-tune the charts, we use the area of control of obstacles. The graph's edges are weighted based on their mobility for wheelchairs and the distance between nodes. As a consequence, we have a graph that precisely reflects the built environment.

**ARWAY Point Cloud**

A point cloud is a collection of millions of data points, each having it's unique (X, Y, Z) coordinates located in the 3D space. Where each individual point is a tiny 3d object represented by basic shapes like a cube or a sphere. In other words, "point clouds are a virtual representation of the feature points found in the real world."

There are numerous approaches to make point cloud maps like Photogrammetry, LiDAR sensors and in any event, utilizing the camera information from our cell phones.

Since nearly everyone owns a smartphone, ARWAY uses smartphone cameras on the back to make a point cloud guide of environmental factors. But there is drawback to use this technique, while it's not being the most precise or the quickest - because of the absence of preparing power - is a significant necessity to drive AR further!

**How ARWAY create point cloud?**

In order to create a point cloud map using smartphone cameras, firstly, it scans the real world for unique features such as patterns, edges, objects, depth, etc using computer vision algorithms. Secondly, those features are then mapped to unique feature points representing that area or place. At the end, millions of such individuals feature points join together to create a point cloud map of the scanned place.

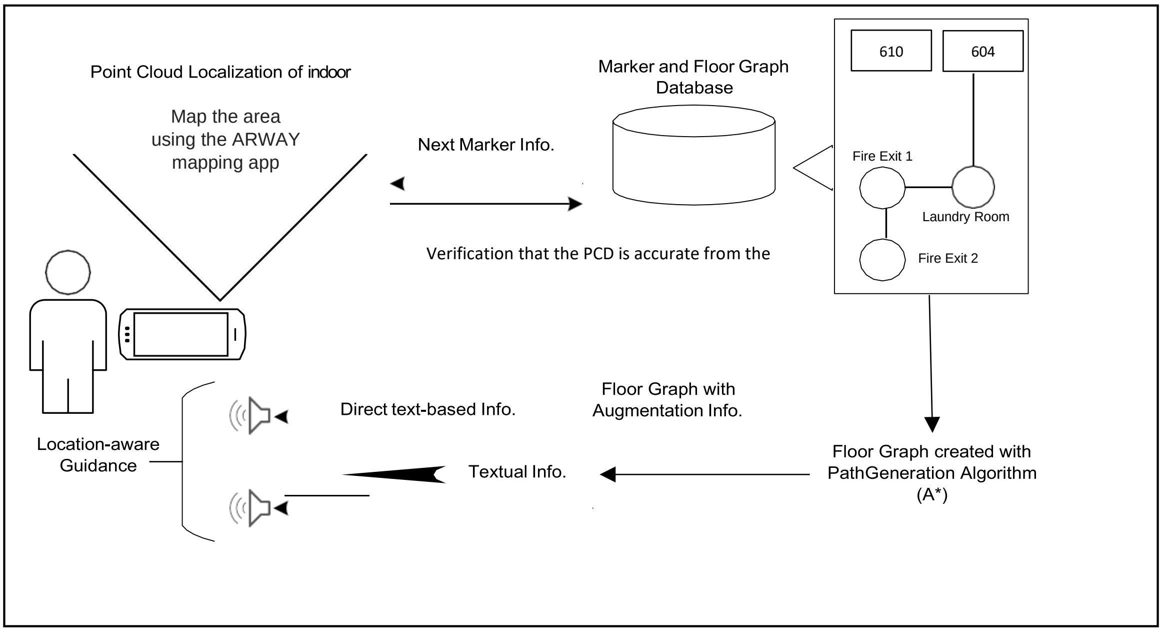
To create point cloud maps, ARWAY implemented ARWAY Mapping application which is available free to download on android or iOS devices. ARWAY Mapping app, which lets you create 3D point cloud maps of the real world by scanning your surrounding using your smartphone. After creating point clouds, during localization user sends the camera image(s) to the ARway cloud service and query for the user's current Pose (position and rotation) in previously mapped area, if the process is successful then in response you get correct local Pose, more details about localization API can be found here.

For a visual positioning tool to be powerful, handling changes in the physical environments and lighting conditions is very important thing. Imagine having to constantly recreate or update a map after every time its environment or lighting condition changes. So, it would be impossible to do and completely impractical for building a large-scale AR-Cloud experience. ARWAY enabling developers to update maps dynamically when a user tries to localize in any of the pre-mapped environments. During localization, the camera keyframes are collected and if the localization is successful then those keyframes are used to extract feature points. This further updates the current maps if needed. Environmental lighting changes from daylight to artificial light indoors or night lights outdoors, these changes affect the accuracy and reliability of any of the feature point-based algorithms that store direct pixels containing light information. This problem can be resolved by using geometry and shapes to represent ‘feature points’ instead of pixels. The histogram of oriented gradients (HOG) which is a feature descriptor used in computer vision and image processing for the purpose of object detection is one of the algorithms showing how this problem can be resolved.

## 3.2 Application Methodology with User Interface

The key aim of this research is to create a device that is simple to use, low-cost, and achieves reliable results with a small amount of computing power. The proposed scheme is depicted in the diagram below, in which a person uses a smartphone application to communicate with point clouds and provides location-based guidance information to the user. This data is saved in the form of a textual summary of the area.

***Block Diagram 1.*** *Overall system for user guidance within an indoor environment.*




The proposed system has the following key aspects.

1. We designed a low-cost navigation system that uses point cloud localization. The point clouds are developed for each unique position for the places in different areas such as Rooms, and corridors, Laundry Room and Fire Exits.

2. The system automatically generates path by detecting and connecting the point clouds with the help of a smartphone camera and creates a graph in the phone by connecting the point clouds.

3. The system has textual information displayed to guide the user upon the recognition of each marker.

4. The user is guided toward a given destination by following a shortest path inside a single or multi-floor building.

5. The system is dynamically extendable. It provides a way to edit an already generated path, and to extend it for incorporating newly deployed markers in the building.

ARWAY creates a highly detailed point cloud map of our surroundings by finding unique feature points that align with the place by looking for unique feature points in the environment such as objects and patters which are a part of that particular surrounding.

Steps for AR Mapping using ARWAY

1. Initially, map the area using the ARWAY mapping app, which is available on both Android/IOS.
2. After creating the map, verify if the created Point Cloud Data stored in the server on the application gives high localization accuracy.
3. After getting localization works, create a pathway using ARWAY web studio.
4. Finally, import SDK in unity and designed the application for end-user's usage.

Figure 2 below shows the PCD map of whole surrounding of 6$^{th}$ floor created using ARWAY mapping application.

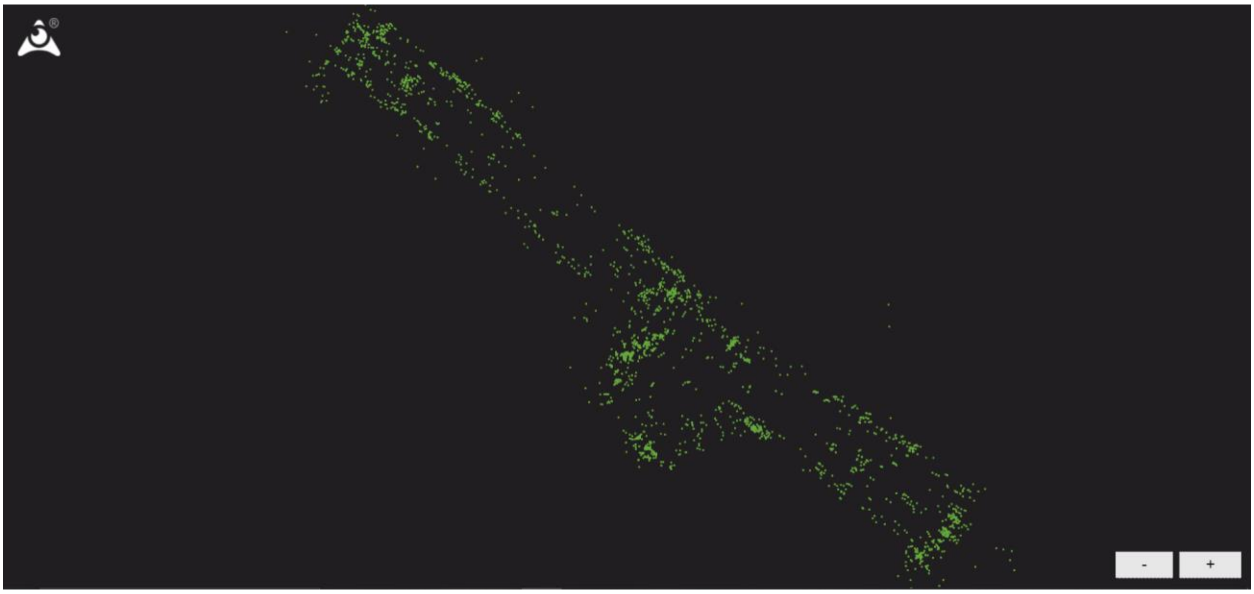


*Figure 2 Point cloud map of 6th floor*

The developer portal in the application shows all the PCD data in form of Map with meta-data associated all the other locations of the surroundings. We can create new charts, update existing maps, add floor plans and 3D assets, waypoints, destinations, text, and more with ARWAY Web Studio. We can also use the online site editor to construct a navigation route by simply dragging and lowering assets to be viewed, which can then be used to navigate around the provided region using the ARWAY SDK program.


*Figure 3 Developer Portal: ARWAY*

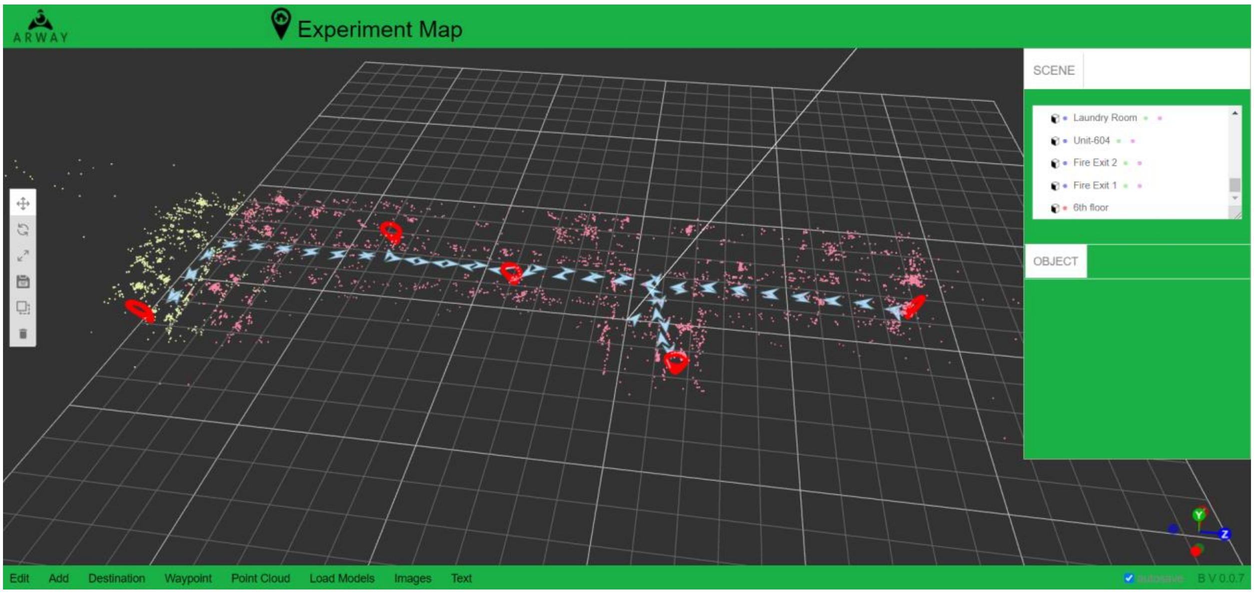



*Figure 4 Experimental Map*

The above experimental map shows the five different locations on the 6th floor surrounding in ARWAY web studio with the created Point Cloud Data (PCD). Finally, using developer unity ARWAY SDK, we made changes on features and performed experiments remotely under the permissions of the department during the COVID19 regulations. The image of the other maps is also available on the application as a user click on it and image will be displayed.


Figure 5 Initialization of Application

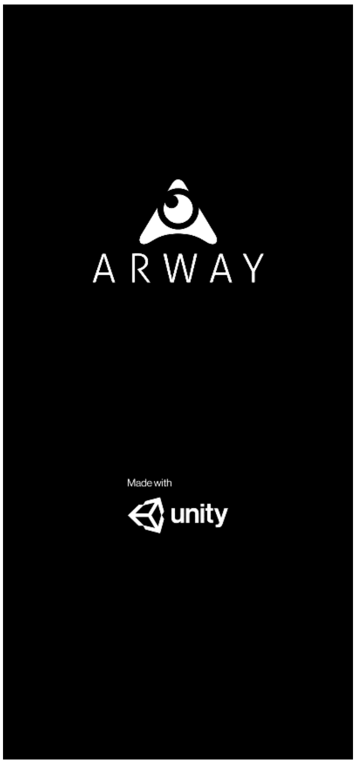



Figure 6 Mapping Mode

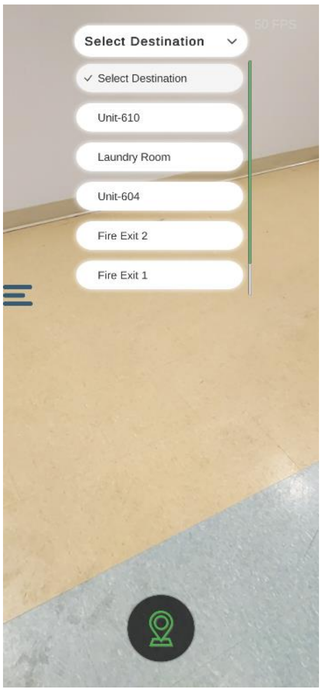



Figure 7 Navigational Options available to users after Mapping Mode

Figure 5-7 shows different screenshots from the smartphone of the application, describing various modules and modes of the proposed system. In the administrative mode the system requires login information. The administrator can do different activities such as to extend the point clouds, delete the maps and update the maps. The other mode is for the end-users to access the locations via their smartphone and navigate in the building through the guidance provided by the application. Different modules of the proposed system are described in the next chapter in details with results and experimentation. Some of these modules are concerned with installation, while others are executed at user side.

# Chapter 4

# Methodology

## 4.1 Objective

In the study, we presented an augmented reality-based indoor navigation application that uses localized environmental features and marker less tracking technologies, as well as the Shortest Pathfinding algorithm with Point Clouds Localization, to help people navigate in indoor environments. The application can be implemented on mobile devices such as a smartphone, providing both visual and textual instructions.

To thoroughly test our system and methods, we conducted both a technical assessment study and a human factors study. The technical evaluation assessed the AR application's effectiveness and dependability. The human factors research looked at things like perceived accuracy, navigation time, subjective ease, subjective workload, and route memory retention. We also wanted to see if Augmented Reality-based navigation system aids were superior to paper maps in terms of navigation time, workload, and comfort, or if Augmented Reality navigation caused poor route retention. These findings may provide scientific evidence to support future indoor navigation system designs. In the final section of our research, we will explore the implications and future research.

The study's key purpose is to distinguish between two indoor navigation techniques: one that uses a 2D-map of the floor and the other that uses an AR mode of navigation. To determine which navigation method would be more effective in getting to the destination in the shortest amount of time. Because by comparing the study through the time difference between the 2d map and AR Application, we can make sure users reached their destination without consuming their time. From a user perspective, ease of use and time saving both are important aspects. So that's why during the application evaluation, we consider the time it took to get to the destination from the beginning key point.

## 4.2 Hypothesis

We conducted the research based on hypothesis statement and its validation to support the research idea and answer the research questions in statistical manner with data driven decision and evidences. A hypothesis will formulate our findings and answering our research question. For some research projects, we might have to write several hypotheses that address different aspects of our research question. Here, we came up with the hypothesis validating which method of indoor navigation is found best by the users through the experiments we conducted.

**Hypothesis H1**

**Null Hypothesis:** There is no significant difference in timings (to reach from starting point to destination point) between using a mobile based AR navigation method and a physical map.

**Alternate Hypothesis:** There is a significant difference in timings (to reach from starting point to destination point) between using a mobile based AR navigation method and a physical map.

## 4.3 Approach and Validation

Numerical Analysis: During the application evaluation, we looked at things like the time it took to get to the destination from the beginning key point.

Subjective Analysis: We performed a subjective study to analyse the user's views regarding the proposed system. In this case, we used a common method of system assessment known as the system usability scale (SUS), which involves applying a 7-point Likert Scale Questionnaire to the various aspects of the application and associated measures, culminating in data that reflects the overall usability of the application.

## 4.4 Questionaries' design

The questionnaire responses were based on selection from 1-7 on a 7-point Likert Scale as shown in the figure 8 below.


*Figure 8 Questionaries' design*

It uses statements about the system usability, answered by the users with numeric values from 1 to 7; where 1 indicates strongly disagree and 7 indicates strongly agree for mobile based AR navigation as well as 2D Physical Maps based navigation. In addition, we also used another simple questionnaire containing more general questions about the users and their background. The questions for each survey were the following.

1. **7-point Likert Scale Questions – Smartphone based AR Application**
   - I was able to localize my device location precisely.
   - I felt an increase in cognitive load while using the application.
   - Arrows and directions were easy to understand.
   - I would use this application in my everyday life.
   - I felt muscle fatigue (tiredness) using this application.

- An augmented reality based indoor navigation system would help me to travel to a new place.
- Is there anything else you would like to add about your experience by using this application?

2. **7-point Likert Scale Questions – 2D Physical Map Navigation**

- I was able to localize my device location precisely.
- I felt an increase in cognitive load while using the physical map.
- I would use digital maps instead of physical maps in a complex building structure.
- I felt muscle fatigue (tiredness) using physical map.
- While I was doing my task, I had to check my location on the physical map every time to make sure I'm not misplaced.
- Is there anything else you would like to add about your experience by using this application?

3. **Demographic Questionnaire about the Users**

- Which category below includes your age?
- What gender do you identify as?
- What is the highest degree or level of school you have completed?
- Have you ever used indoor navigation applications before?
- In your daily life, how often do you use maps (Digital map or Paper map)?
- Have you ever used to google map’s AR navigation?
- Do you have experience with mobile AR (Augmented Reality) or AR headset?
- If you use maps what is your preference digital maps or paper maps?
- Have you ever used indoor maps which placed inside the building?

## 4.5 Participant recruitment

Participants were the residents of the apartment building. During the experiment, each participant had to wear a mask while performing their given task. Moreover, to ensure each participant's safety, a researcher will be sanitizing each common touchpoint (doorknobs, elevator buttons, door handle) before and after the experiment that individuals can affect.

1. In order to perform experiments remotely during the pandemic, there are some requirements for participants. Any interested person who has an android phone with the following requirements listed on (https://developers.google.com/ar/devices) here; can participate in the study. (If they have the following requirements fulfilled, those will be selected.) Participants were recruited by sending a poster to a group of people; through social media and phone calls.

   So, for those who are performing tasks through AR prototype, they have to wear a smartwatch to note timing to perform each task on the side on their notes and submitted to the researcher after completing their task, or also they can use screen recording. It same for those who have a stopwatch/smartwatch can participate in performing tasks through a 2d map, and if they are comfortable using a phone timer, they can use it and note the timing. All the details to the interested person send it through an email.

2. After recruiting the participants who meet the above requirements, those will be divide into two groups using a random selection method by the researcher, where one group had to use a 2d map, and another will be in the AR group.
3. After dividing participants into two groups, the researcher sends all the experiment task details and the APK file to each group accordingly through email; with created a google timesheet to choose their preferred day and time to perform their given task.
4. Each participant can take up to 5-7 minutes to complete the given task by filling out all the questionnaires. So, there is a 15-minute difference between each participant's timing.

## 4.6 Steps to perform task with 2D Map

1. Fill out demographic questionnaire.
2. Then clicking on 2D map on app which will navigate them to 2D floor image.
3. From starting position to unit -610, from unit-610 to laundry room, to 604, to fire exit.
4. When they start performing the task had to start stop watch and note the timing when they reach to 610 first then 610-laundry room and so on. (Note timing of every path they are navigating) All the participants use stop watch/smartwatch during the task.
5. After completing the task, they have to fill out 7-point Likert scale questionnaire and send those notes to researcher who is available on zoom they have to just click on link it will navigate them to researcher and send those timing.

## 4.7 Steps to perform experiment with mobile based AR application

1. Fill out demographic.
2. Open the application and click on experiment map from list of available maps.
3. Start screen recording/smart watch.
4. Click on localize button.
5. Start navigate their given task.
6. After completing the task, they have to fill out 7-point Likert scale questionnaire and send those notes to researcher who is available on zoom they have to just click on link it will navigate them to researcher and send those timing.

## 4.8 Selected Paths

**Path 1:** This path goes from the elevator on 6$^{th}$ floor up to unit-610.

**Path 2:** From unit 610 participant need to follow path to the laundry room on the same 6$^{th}$ floor.

**Path 3:** It goes from laundry room to unit 604. (On 6$^{th}$ floor)

**Path 4:** This path goes from unit 604- to exit stair-B (Fire Exit-B)

*Table 3 Selected Paths*

| PATH | DISTANCE |
|---|---|
| PATH-1 | 8.57m |
| PATH-2 | 11.15m |
| PATH-3 | 4.75m |
| PATH-4 | 7.36m |

There were total 24 participants, 4 participate for pilot study and gave a feedback and from remaining 20 participants 10 chose 2D map 10 chose AR based navigation.

# Chapter 5

# Results and Analysis

In the previous chapter, we discussed the hypothesis that we will validate to answer our research questions, the methodology and complete procedures for setting and collecting the data for the experiments with all the steps.

In this chapter, we will be discussing the results of the experiments we conducted for the evaluation of our mobile based AR application. There were total 20 number of participants, out of which 10 chose to use the Physical 2D map indoor navigation and 10 chose AR based application. The table 4 and figure 9 below shows the results of the user experiments for AR based Indoor Navigation.

*Table 4 Detail of user guidance evaluation on each path for AR based Indoor Navigation*

| User | Localization Time | PATH | TIME TAKEN(S) |
|---|---|---|---|
| User 1 | 14.95 | PATH-1 | 14.3 |
| | | PATH-2 | 6.44 |
| | | PATH-3 | 4.74 |
| | | PATH-4 | 8.8 |
| User 2 | 10.3 | PATH-1 | 10.12 |
| | | PATH-2 | 13.76 |
| | | PATH-3 | 6.23 |
| | | PATH-4 | 5.52 |
| User 3 | 17.27 | PATH-1 | 8.93 |
| | | PATH-2 | 10.4 |
| | | PATH-3 | 5.73 |
| | | PATH-4 | 8.53 |
| User 4 | 17.28 | PATH-1 | 12.92 |
| | | PATH-2 | 12.05 |
| | | PATH-3 | 7.65 |
| | | PATH-4 | 12.48 |
| User 5 | 15.61 | PATH-1 | 9.52 |
| | | PATH-2 | 9.81 |
| | | PATH-3 | 4.92 |
| | | PATH-4 | 9.51 |
| User 6 | 17.84 | PATH-1 | 14.86 |
| | | PATH-2 | 9.95 |
| | | PATH-3 | 7.52 |
| | | PATH-4 | 13.05 |
| User 7 | 19.98 | PATH-1 | 13.98 |
| | | PATH-2 | 12.1 |
| | | PATH-3 | 8.24 |
| | | PATH-4 | 12.4 |
| User 8 | 18.71 | PATH-1 | 14.38 |
| | | PATH-2 | 14.11 |
| | | PATH-3 | 7.4 |
| | | PATH-4 | 19.96 |
| User 9 | 16.52 | PATH-1 | 12.4 |
| | | PATH-2 | 15.21 |
| | | PATH-3 | 7.23 |
| | | PATH-4 | 10.52 |
| User 10 | 18.4 | PATH-1 | 11.27 |
| | | PATH-2 | 15.76 |
| | | PATH-3 | 5.23 |
| | | PATH-4 | 9.52 |

| User | Localization Time | PATH | TIME TAKEN(S) |
|---|---|---|---|
| S | 14.95 | PATH-1 | 14.3 |
| | | PATH-2 | 6.44 |
| | | PATH-3 | 4.74 |
| | | PATH-4 | 8.8 |
| P | 10.3 | PATH-1 | 10.12 |
| | | PATH-2 | 13.76 |
| | | PATH-3 | 6.23 |
| | | PATH-4 | 5.52 |
| V | 17.27 | PATH-1 | 8.93 |
| | | PATH-2 | 10.4 |
| | | PATH-3 | 5.73 |
| | | PATH-4 | 8.53 |
| K | 17.28 | PATH-1 | 12.92 |
| | | PATH-2 | 12.05 |
| | | PATH-3 | 7.65 |
| | | PATH-4 | 12.48 |
| N | 15.61 | PATH-1 | 9.52 |
| | | PATH-2 | 9.81 |
| | | PATH-3 | 4.92 |
| | | PATH-4 | 9.51 |
| P | 17.84 | PATH-1 | 14.86 |
| | | PATH-2 | 9.95 |
| | | PATH-3 | 7.52 |
| | | PATH-4 | 13.05 |
| D | 19.98 | PATH-1 | 13.98 |
| | | PATH-2 | 12.1 |
| | | PATH-3 | 8.24 |
| | | PATH-4 | 12.4 |
| M | 18.71 | PATH-1 | 14.38 |
| | | PATH-2 | 14.11 |
| | | PATH-3 | 7.4 |
| | | PATH-4 | 19.96 |
| A | 16.52 | PATH-1 | 12.4 |
| | | PATH-2 | 15.21 |
| | | PATH-3 | 7.23 |
| | | PATH-4 | 10.52 |
| J | 18.4 | PATH-1 | 11.27 |
| | | PATH-2 | 15.76 |
| | | PATH-3 | 5.23 |
| | | PATH-4 | 9.52 |

*Figure 9 Detail of user guidance evaluation on each path for AR based Indoor Navigation*

Figure 10 below shows the Physical Map of the floor which was provided to the users who chose 2D Physical map Indoor Navigation.


*Figure 10 Physical Map of the floor*

Table 5 and figure 11 below shows the results of the user experiments for 2D Physical Map

*Table 5 User Experiments for 2D Physical Map based Indoor Navigation*

| USER ID | PATH | TIME TAKEN(S) |
|---|---|---|
| **User 1** | PATH-1 | 16.57 |
| | PATH-2 | 27.71 |
| | PATH-3 | 15.26 |
| | PATH-4 | 11.22 |
| **User 2** | PATH-1 | 11.98 |
| | PATH-2 | 38.38 |
| | PATH-3 | 8.65 |
| | PATH-4 | 24.69 |
| **User 3** | PATH-1 | 10.75 |
| | PATH-2 | 19.16 |
| | PATH-3 | 9.3 |
| | PATH-4 | 13.11 |
| **User 4** | PATH-1 | 12.7 |
| | PATH-2 | 17.01 |
| | PATH-3 | 8.33 |
| | PATH-4 | 19.1 |
| **User 5** | PATH-1 | 9.06 |
| | PATH-2 | 21.93 |
| | PATH-3 | 11.1 |
| | PATH-4 | 16.4 |
| **User 6** | PATH-1 | 18.14 |
| | PATH-2 | 26.53 |
| | PATH-3 | 17.94 |
| | PATH-4 | 15.84 |
| **User 7** | PATH-1 | 17.94 |
| | PATH-2 | 24.71 |
| | PATH-3 | 12.23 |
| | PATH-4 | 16.72 |
| **User 8** | PATH-1 | 19.4 |
| | PATH-2 | 22.15 |
| | PATH-3 | 15.56 |
| | PATH-4 | 15.22 |
| **User 9** | PATH-1 | 17.57 |
| | PATH-2 | 21.71 |
| | PATH-3 | 13.28 |
| | PATH-4 | 15.32 |
| **User 10** | PATH-1 | 16.57 |
| | PATH-2 | 27.71 |
| | PATH-3 | 15.26 |
| | PATH-4 | 11.22 |

| USER ID | PATH | TIME TAKEN(S) |
|---|---|---|
| User 1 | PATH-1 | 16.57 |
| | PATH-2 | 27.71 |
| | PATH-3 | 15.26 |
| | PATH-4 | 11.22 |
| User 2 | PATH-1 | 11.98 |
| | PATH-2 | 38.38 |
| | PATH-3 | 8.65 |
| | PATH-4 | 24.69 |
| User 3 | PATH-1 | 10.75 |
| | PATH-2 | 19.16 |
| | PATH-3 | 9.3 |
| | PATH-4 | 13.11 |
| User 4 | PATH-1 | 12.7 |
| | PATH-2 | 17.01 |
| | PATH-3 | 8.33 |
| | PATH-4 | 19.1 |
| User 5 | PATH-1 | 9.06 |
| | PATH-2 | 21.93 |
| | PATH-3 | 11.1 |
| | PATH-4 | 16.4 |
| User 6 | PATH-1 | 18.14 |
| | PATH-2 | 26.53 |
| | PATH-3 | 17.94 |
| | PATH-4 | 15.84 |
| User 7 | PATH-1 | 17.94 |
| | PATH-2 | 24.71 |
| | PATH-3 | 12.23 |
| | PATH-4 | 16.72 |
| User 8 | PATH-1 | 19.4 |
| | PATH-2 | 22.15 |
| | PATH-3 | 15.56 |
| | PATH-4 | 15.22 |
| User 9 | PATH-1 | 17.57 |
| | PATH-2 | 21.71 |
| | PATH-3 | 13.28 |
| | PATH-4 | 15.32 |
| User 10 | PATH-1 | 16.57 |
| | PATH-2 | 27.71 |
| | PATH-3 | 15.26 |
| | PATH-4 | 11.22 |

*Figure 11 User Experiments for 2D Physical Map based Indoor Navigation*

Next, we calculated the time differences among the users for each path while using AR application and 2D physical Map. The figure 12 and 13 below shows the comparison of time taken for each path by all the users while using AR application and 2D physical Map. It can be concluded that AR map users find it very efficient and time saving while navigating using the application as compared to the 2D physical maps, as the difference is positive for 92.5% measured readings. For some of the readings, there is quite much difference because navigating from one to place to another using a physical map doesn’t provide any assistance and the user has to search for the right directions looking at the structure of the path, on the other hand in case of an AR based assisted navigation, it is a whole different situation where user has to just select the initial and final point and then look for the assistance and information shared by the application.

| USER ID | PATH | TIME TAKEN(S) - AR APP | TIME TAKEN(S)- 2D MAP | Time Difference (AR App - 2D Map) |
|---|---|---|---|---|
| User 1 | PATH-1 | 14.3 | 16.57 | 2.27 |
| | PATH-2 | 6.44 | 27.71 | 21.27 |
| | PATH-3 | 4.74 | 15.26 | 10.52 |
| | PATH-4 | 8.8 | 11.22 | 2.42 |
| User 2 | PATH-1 | 10.12 | 11.98 | 1.86 |
| | PATH-2 | 13.76 | 38.38 | 24.62 |
| | PATH-3 | 6.23 | 8.65 | 2.42 |
| | PATH-4 | 5.52 | 24.69 | 19.17 |
| User 3 | PATH-1 | 8.93 | 10.75 | 1.82 |
| | PATH-2 | 10.4 | 19.16 | 8.76 |
| | PATH-3 | 5.73 | 9.3 | 3.57 |
| | PATH-4 | 8.53 | 13.11 | 4.58 |
| User 4 | PATH-1 | 12.92 | 12.7 | -0.22 |
| | PATH-2 | 12.05 | 17.01 | 4.96 |
| | PATH-3 | 7.65 | 8.33 | 0.68 |
| | PATH-4 | 12.48 | 19.1 | 6.62 |
| User 5 | PATH-1 | 9.52 | 9.06 | -0.46 |
| | PATH-2 | 9.81 | 21.93 | 12.12 |
| | PATH-3 | 4.92 | 11.1 | 6.18 |
| | PATH-4 | 9.51 | 16.4 | 6.89 |
| User 6 | PATH-1 | 14.86 | 18.14 | 3.28 |
| | PATH-2 | 9.95 | 26.53 | 16.58 |
| | PATH-3 | 7.52 | 17.94 | 10.42 |
| | PATH-4 | 13.05 | 15.84 | 2.79 |
| User 7 | PATH-1 | 13.98 | 17.94 | 3.96 |
| | PATH-2 | 12.1 | 24.71 | 12.61 |
| | PATH-3 | 8.24 | 12.23 | 3.99 |
| | PATH-4 | 12.4 | 16.72 | 4.32 |
| User 8 | PATH-1 | 14.38 | 19.4 | 5.02 |
| | PATH-2 | 14.11 | 22.15 | 8.04 |
| | PATH-3 | 7.4 | 15.56 | 8.16 |
| | PATH-4 | 19.96 | 15.22 | -4.74 |
| User 9 | PATH-1 | 12.4 | 17.57 | 5.17 |
| | PATH-2 | 15.21 | 21.71 | 6.5 |
| | PATH-3 | 7.23 | 13.28 | 6.05 |
| | PATH-4 | 10.52 | 15.32 | 4.8 |
| User 10 | PATH-1 | 11.27 | 16.57 | 5.3 |
| | PATH-2 | 15.76 | 27.71 | 11.95 |
| | PATH-3 | 5.23 | 15.26 | 10.03 |
| | PATH-4 | 9.52 | 11.22 | 1.7 |

*Figure 12 Comparison of Time Taken for each path while using AR application and 2D physical Map*

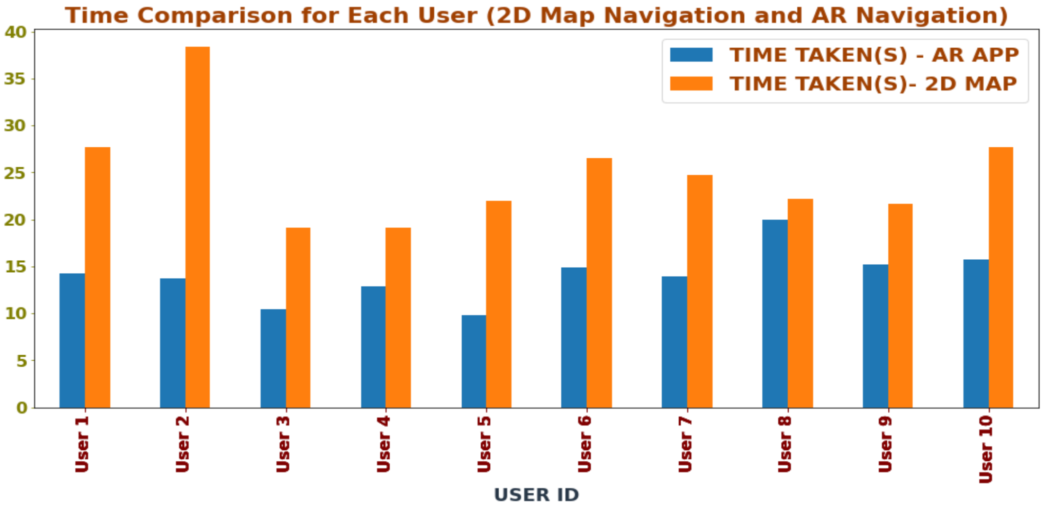



*Figure 13 Comparison of Time taken on a bar-graph*

We also visualised the time differences for each user in a cumulative bar plot to shows the differences in more interpretable manner as shown in the figure 14.

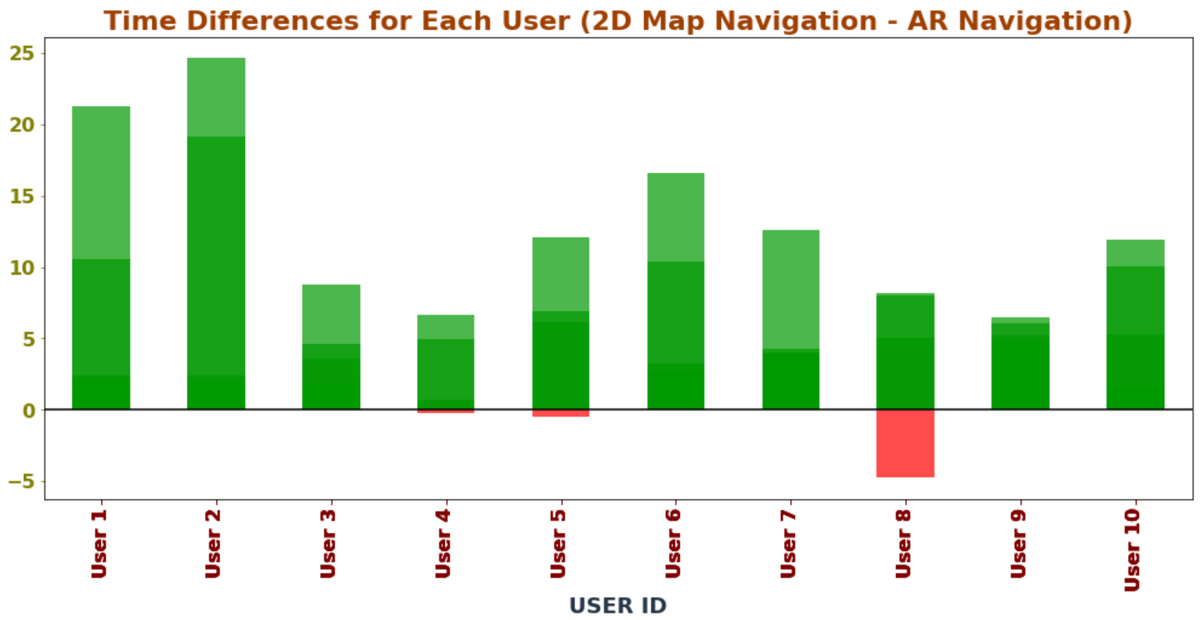



*Figure 14 Time Differences for Each User (2D Map Navigation - AR Navigation)*

Figure 15 shows the descriptive statistics of the three columns time taken while navigating with the AR App, time taken while navigating with the 2D map and the time differences. It can be seen that the mean of time taken using the AR map is 10.43 seconds whereas for the 2D map it is 17.08 seconds, which depicts there is almost double time taken in general while navigating with the 2D physical Map. The similar statistic is shown by the standard deviation which supports the above evidence. The other quantile statistics such as min, 25%, 50% and 75% quantiles also represent the same scenario which validates that there is a huge difference between the time taken while navigating with 2D maps and AR application.

| Variable | count | mean | std | min | 25% | 50% | 75% | max |
|---|---|---|---|---|---|---|---|---|
| TIME TAKEN(S) - AR APP | 40 | 10.4363 | 3.5168 | 4.74 | 7.6175 | 10.035 | 12.953 | 19.96 |
| TIME TAKEN(S)- 2D MAP | 40 | 17.0858 | 6.2151 | 8.33 | 12.583 | 16.485 | 19.22 | 38.38 |
| Time Difference (AR App - 2D Map) | 40 | 6.6495 | 5.9852 | -4.74 | 2.6975 | 5.095 | 9.0775 | 24.62 |

*Figure 15 Descriptive statistics of AR app and 2D map*

## 5.1 Mobile based AR Application Navigation

It can be observed that 10 out of 10 users were able to find their location precisely using the AR navigation.

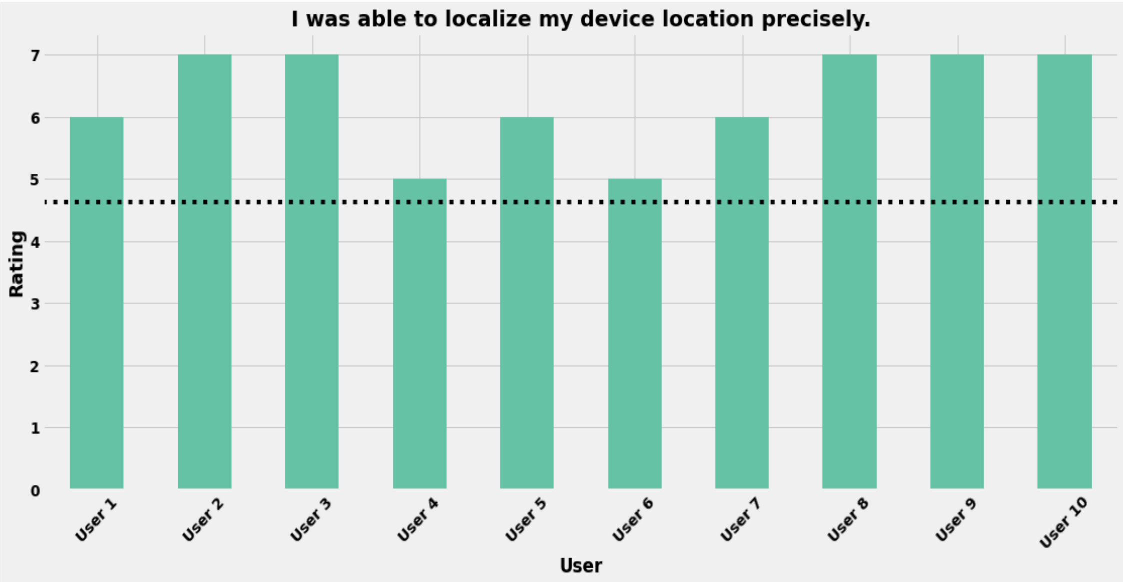



*Figure 16 Technical Question 1 responses (1-7) - AR based Navigation*

It can be observed that 0 out of 10 users felt cognitive load while using the application.

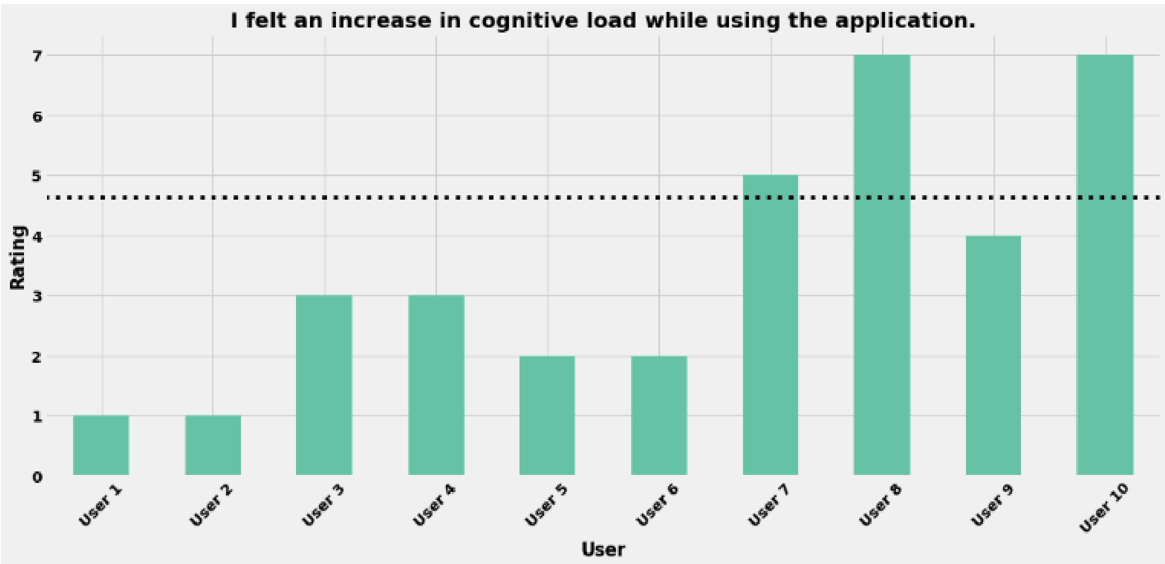



*Figure 17 Technical Question 3 responses (1-7) - AR based Navigation*

It can be observed that 9 out of 10 users find the arrows and pointing directions of the AR navigation easy to understand.

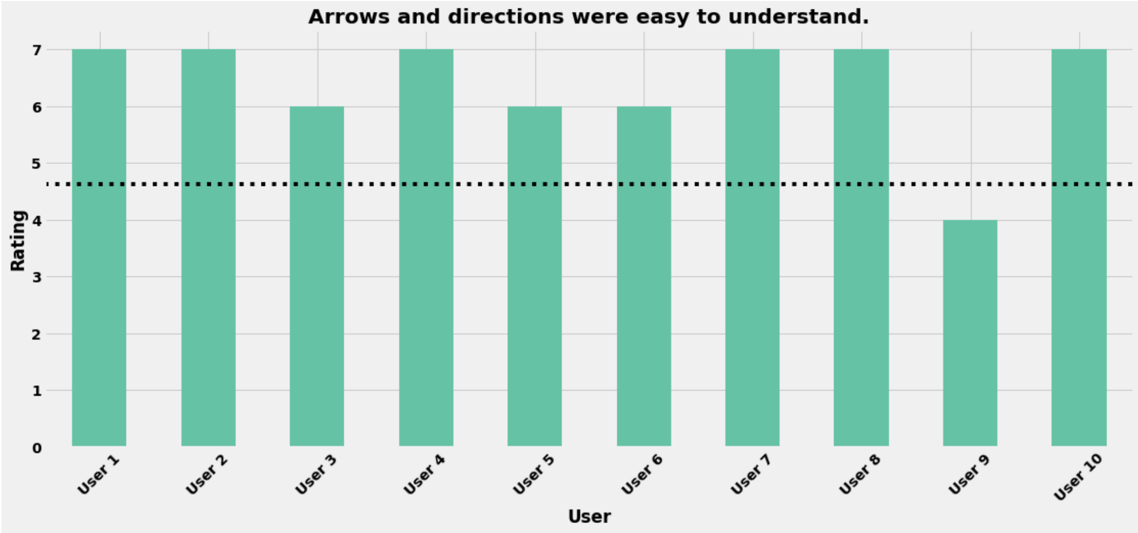



*Figure 18 Technical Question 4 responses (1-7) - AR based Navigation*

It can be observed that 10 out of 10 users would prefer to use the application on everyday basis.

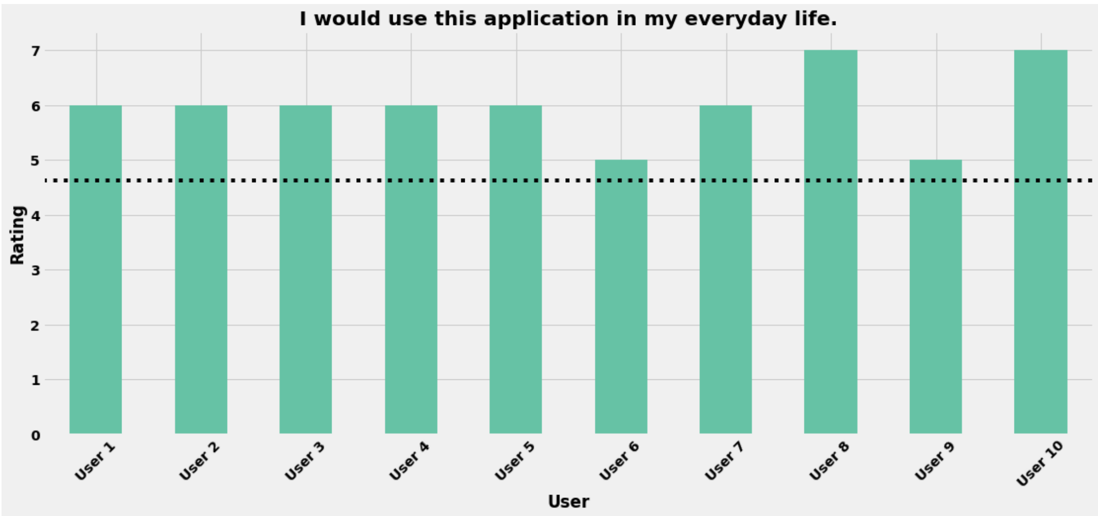



*Figure 19 Technical Question 5 responses (1-7) - AR based Navigation*

It can be observed that 1 out of 10 users felt muscle fatigue (tiredness) while using the application.

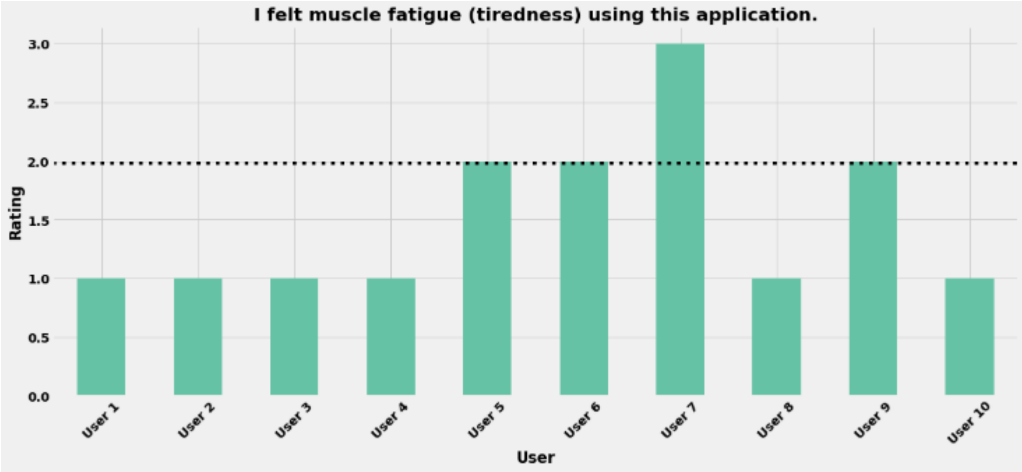



*Figure 20 Technical Question 6 responses (1-7) - AR based Navigation*

It can be observed that 10 out of 10 users believe that Augmented Reality based Navigation system would help them to travel new places.

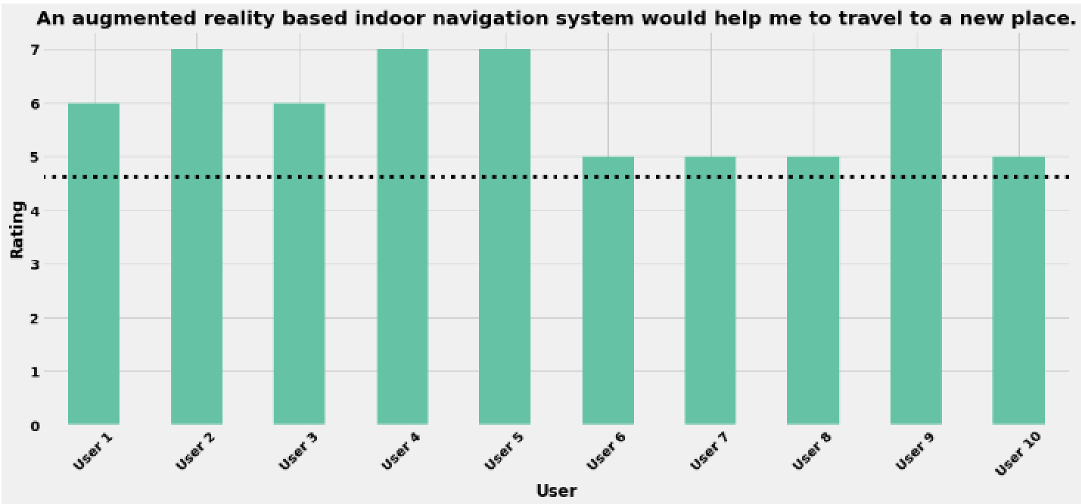



*Figure 21 Technical Question 7 responses (1-7) - AR based Navigation*

We also calculated the Mean Scale Ratings for the responses recorded as shown in table 6.

*Table 6 Average Response (1-7) for AR based navigation Questionnaire*

| Question | Scale (1-7) |
|---|---|
| **I was able to localize my device location precisely.** | 6.3 |
| **I was able to localize my device location precisely.** | 6.2 |
| **I felt an increase in cognitive load while using the application.** | 3.5 |
| **Arrows and directions were easy to understand.** | 6.4 |
| **I would use this application in my everyday life.** | 6.0 |
| **I felt muscle fatigue (tiredness) using this application.** | 1.5 |
| **An augmented reality based indoor navigation system would help me to travel to a new place.** | 6.0 |

## 5.2 2D Physical Map based Navigation

Figure 22 to 26 below shows the subjective analysis of the responses recorded through questionnaire for the 2D physical Map Based navigation. The responses are recorded on a Likert scale from 1-7, we chose 66.6% as the reference line for considering the responses to be highly positive or highly negative.

It can be observed that 10 out of 10 users were able to find their location precisely using the 2D Physical map.

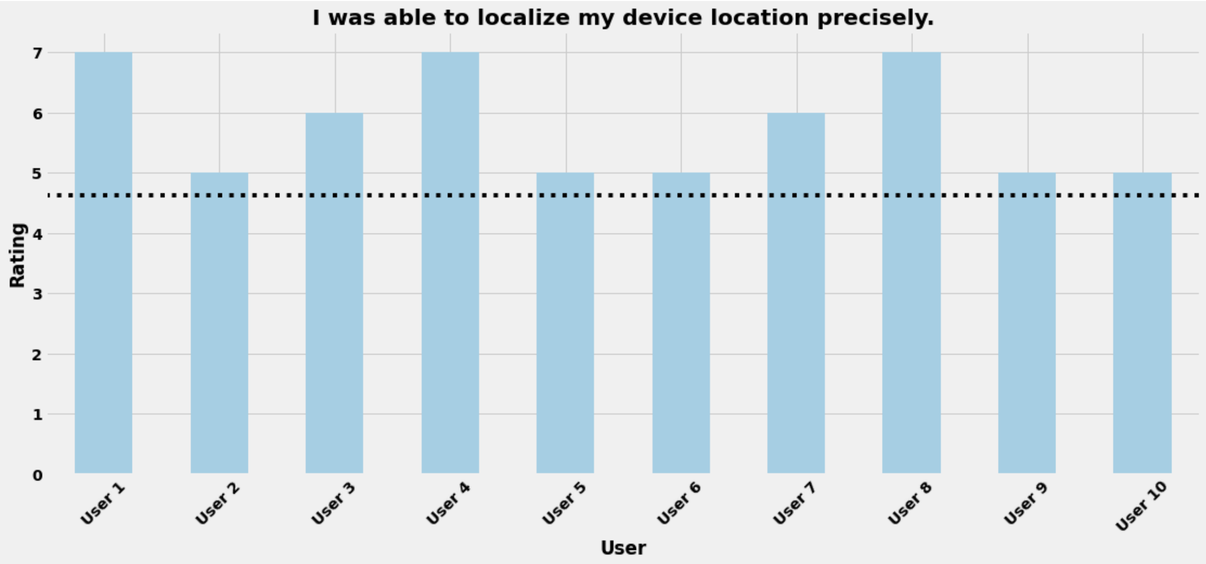



*Figure 22 Technical Question 1 responses (1-7) - 2D Physical Map based Navigation*

It can be observed that 7 out of 10 users felt cognitive load while using the application.

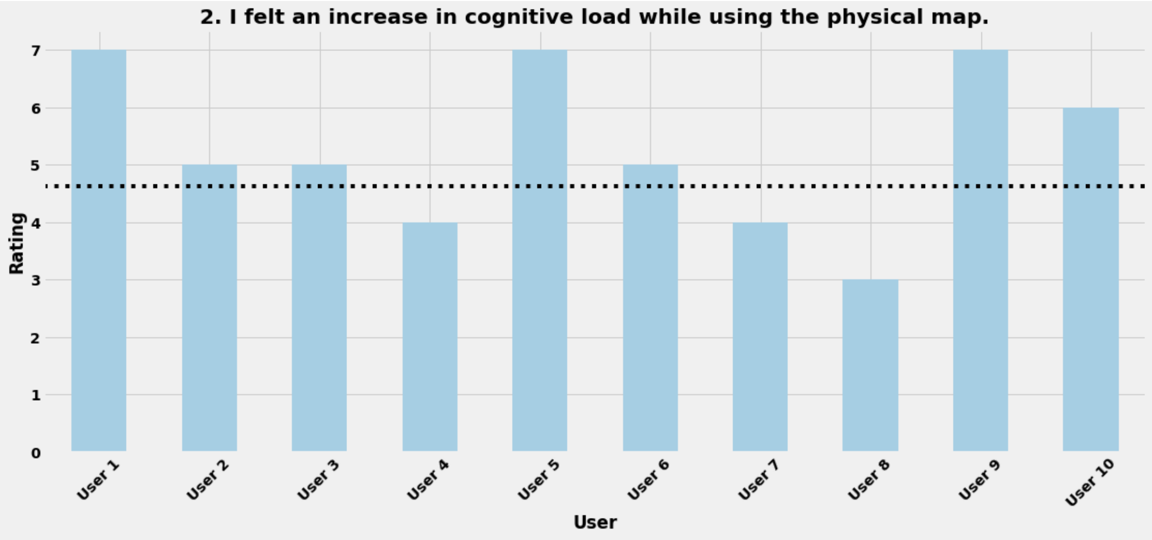



*Figure 23 Technical Question 2 responses (1-7) - 2D Physical Map based Navigation*

It can be observed that 10 out of 10 users would prefer digital maps instead of using 2D maps in complex building.

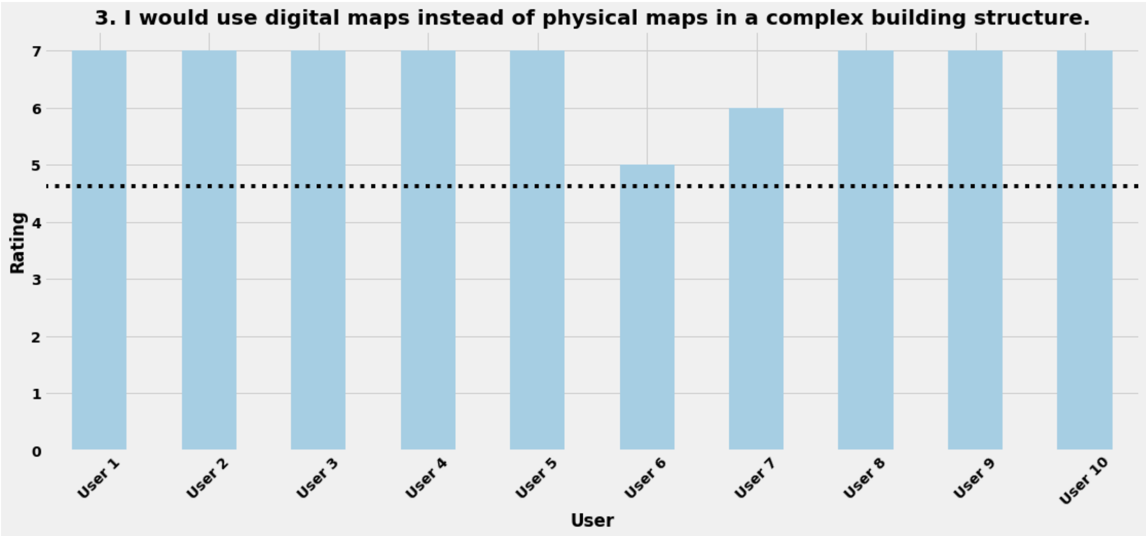



*Figure 24 Technical Question 3 responses (1-7) - 2D Physical Map based Navigation*

It can be observed that 3 out of 10 users felt muscle fatigue (tiredness) while using the 2D map.

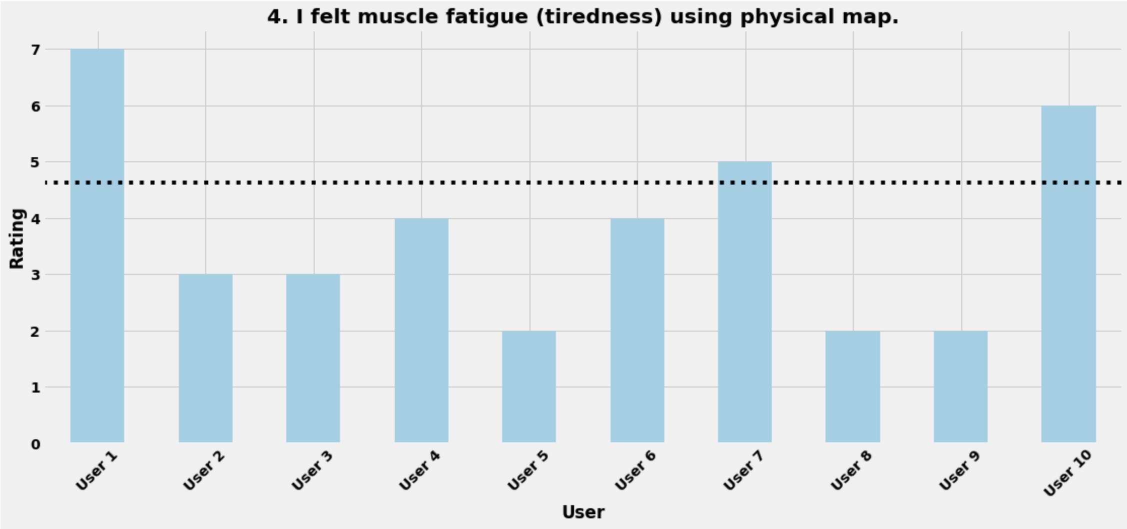



*Figure 25 Technical Question 4 responses (1-7) - 2D Physical Map based Navigation*

It can be observed that 7 out of 10 users felt that they had to check into the 2D map from time to time to look into the application.

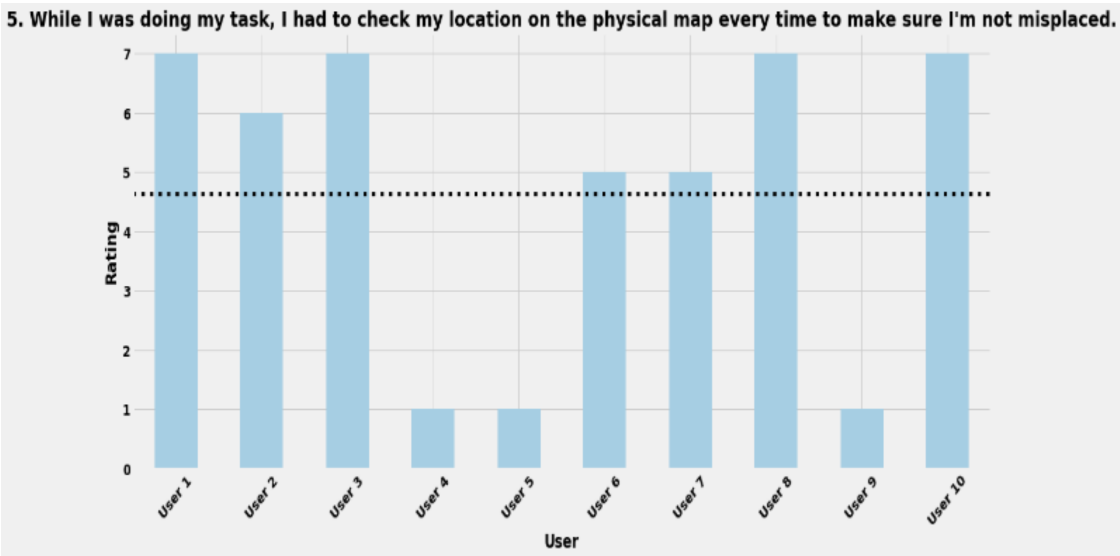



*Figure 26 Technical Question 5 responses (1-7) - 2D Physical Map based Navigation*

We also calculated the Mean Scale Ratings for the responses recorded as shown in table 7.

*Table 7 Average Response (1-7) for 2D Map based navigation Questionnaire*

| Question | Scale (1-7) |
|---|---|
| **I was able to localize my device location precisely.** | 5.8 |
| **2. I felt an increase in cognitive load while using the physical map.** | 5.3 |
| **3. I would use digital maps instead of physical maps in a complex building structure.** | 6.7 |
| **4. I felt muscle fatigue (tiredness) using physical map.** | 3.8 |
| **5. While I was doing my task, I had to check my location on the physical map every time to make sure I'm not misplaced.** | 4.7 |

## 5.3 Demographic Questionnaire

Figure 27 to 33 below shows the information regarding demography of the users. It can be seen that 16 users were from age group 19-25 and 4 users were from the age group 26-39. There were 10 males and 10 females in the survey. There were 8 people with Bachelor's degree, 8 people with High School degree and 4 people with Master's degree in the survey. Out of all the people 8 have already used AR based application while 12 people haven't used AR based application. Out of 20 people 10 people have already used Google Map AR functionality.  Also, the majority of our survey participants uses map frequently. 10 people had experience of using AR headset, 8 people didn't even know about AR headset, on the other hand, there were two people who knew about the AR headset by never used it before.

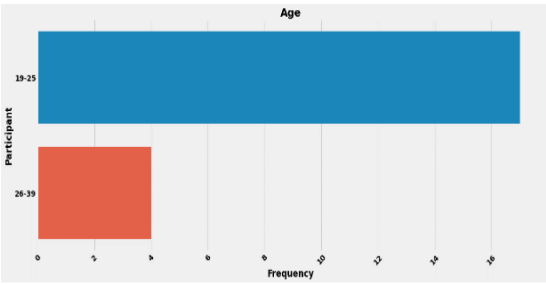



*Figure 27 Age of Participants*

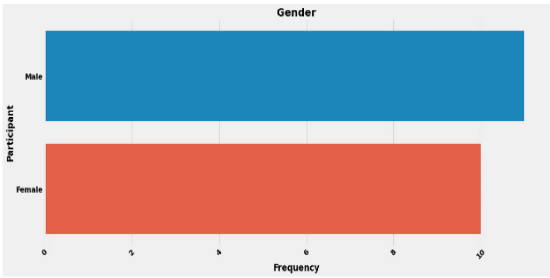



*Figure 28 Gender of Participants*

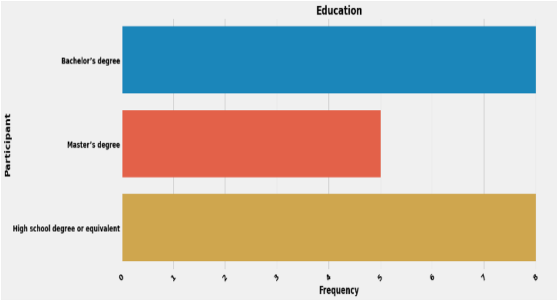



*Figure 29 Education Level of Participants*

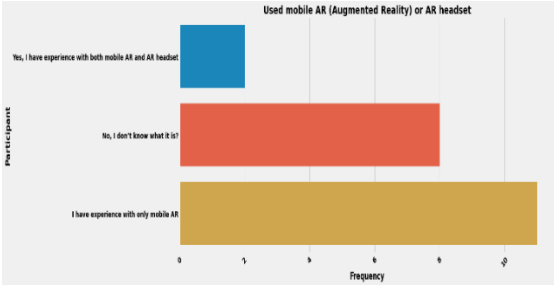



*Figure 33 Used google AR headset before or not*

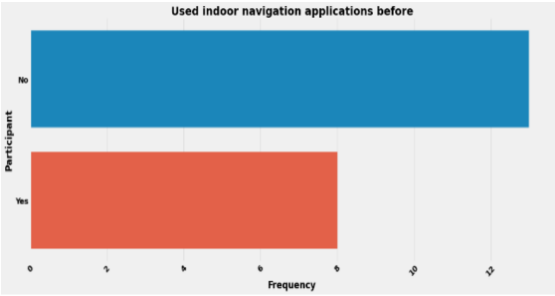



*Figure 30  whether the user used Indoor Navigation before or not*

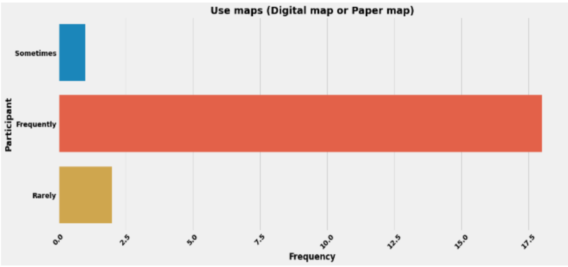



*Figure 31 whether the user used 2D Maps before or not*

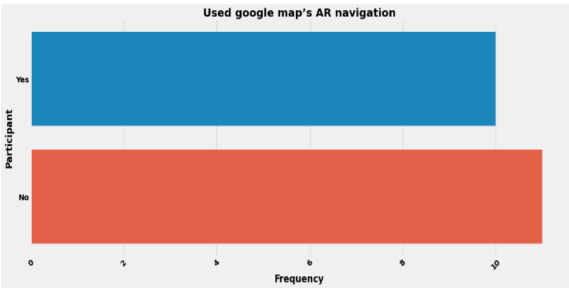



*Figure 32 whether the user used google Map's AR before or not*

## 5.4 Statistical Analysis

We also conducted the statistical analysis on the time differences and time taken using the AR application and 2D maps. In this section of this chapter, we will discuss the statistical analysis results.

Experiment measurement Validations are probabilistic, and they are performed by finding trends in data and using statistical methods. There's a possibility that experiments, which include taking samples from a population, could reveal an impact caused by sampling errors. If the observed effect has a p-value of less than 0.05 (95 percent confidence interval (CI)), it can be concluded that the observed effect represents the characteristics of the entire population. If the p-value is greater than 0.05, though, the observed effect does not represent the characteristics of the entire population. Statistical significance tests are used to determine if the discrepancies between the groups under study are meaningful or merely coincidental. As a result, we looked at statistical analysis of the experiment's results to see if there was a statistically meaningful discrepancy in the mean values of the output parameters obtained. To assess the presence of these statistically important output variations, a one-way study of variance, or ANOVA, was used.

To conduct this analysis, therefore, the data must meet the following criteria:

(a) Normal distribution;

(b) Homogeneous variance;

(c) Lack of major outliers; and

(d) Observational freedom.

To check for data normality, a qq-plot was produced as shown in the figure 34 below which suggests that the data is normal and has homogeneous variances and no outliers.

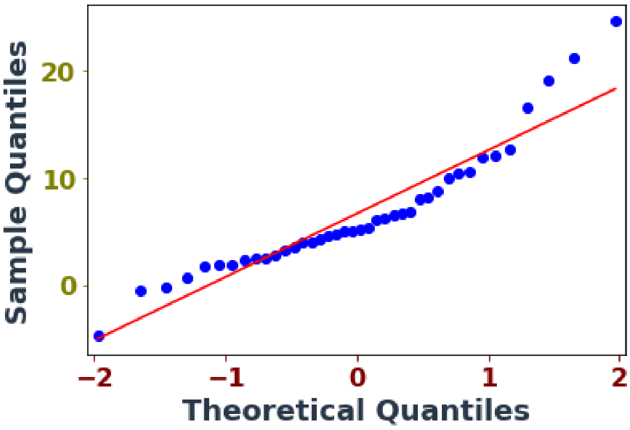



*Figure 34 QQ Plot - Normality Check*

If no statistically meaningful difference is present in the mean value of the output measures for the various models under analysis, the null hypothesis (H0) that there is no significant difference in timings (to reach from starting point to destination point) between using a mobile based AR navigation method and a physical map is accepted. If a statistically relevant performance difference ($P < 0.05$) is discovered, the alternative explanation (H1) is accepted and H0 is refused. To conduct statistical analyses, we used a Python script.

We conducted independent sample T-test for the time differences. The t test (also called Student's T Test) compares two averages (means) and tells if they are different from each other. The t test also tells how significant the differences are. In other words, it lets us know if those differences could have happened by chance.

A large t-score tells that the groups are different. A small t-score tells that the groups are similar. We found the following results while running the t-test on time taken for AR application and 2D map navigation.

```
t-statistics:  -5.889177893067742

D.O.F.:  78

CV:  1.6646246444385238

P-Value:  9.294049241326263e-08

t=-5.889, df=78, cv=1.665, p=0.000
```

Based on the p-value, we rejected the null hypothesis that the means are not equal, there is significant difference across the models. Finally, we conducted the one-Way ANOVA for which also the p-value was found to be to very low than confidence interval of 0.05. Hence, we can reject the Null Hypothesis and accept the alternate hypothesis – that there is a significant difference in timings (to reach from starting point to destination point).

To conduct results and analysis of demographic, technical and human factors study; we use following APIs,

1. Pandas for data manipulation and mugging where pandas is an open-source library that is used to analyze data. It takes CSV (comma-separated values) or SQL database, and creates an object with rows and columns which called a data frame.
2. NumPy and Scipy for numerical operations, in which NumPy is a Python library utilized for working with arrays. It additionally has capacities for working in domain of linear algebra, Fourier transform, and matrices. Where SciPy is a collection of numerical calculations and convenience functions built based on the NumPy expansion of Python.
3. Matplotlib and Seaborn for data visualizations; Matplotlib is mainly deployed for basic plotting. Visualization using Matplotlib generally consists of bars, pies, lines, scatter

plots and so on. Seaborn: Seaborn, on the other hand, provides a variety of visualization patterns. It uses fewer syntax and has easily interesting default themes.

There were also many base python modules we used, but the above is widely used.

# Chapter 6

# Conclusions

The main objective of an indoor navigation and localization system is to reliably and accurately localize users in an indoor environment and to direct them from point A to point B in an effective and straightforward manner. We asked users to navigate through four different paths in our experiments. The system's robustness is ensured by comparing the AR app's time differences with the 2D map navigation. Similarly, the efficiency can be measured via counting the time differences to reach a destination. Subjective analysis also helped to evaluate other qualitative features of the system which we did in the later part of our research.

Figure 12 and 13 shows the results of our experiments. Ten users performed the experiments by navigating through four different paths using 2D physical maps while 10 people performed the experiments while navigating using the AR application. For 92.5% of the observations, the time taken while navigating with the AR application was considerable lesser than the time taken for the navigation with the 2D maps. So, the time taken by each user for each path was also satisfactory as compared to the 2D maps. The results revealed that the proposed methodology is efficient, robust and accurate. The user satisfaction, system usability, ease of use and freedom in mobility were evaluated through subjective analysis through the surveys and questionnaire. For the subjective analysis, it was found that 90% of the users rated the proposed system reliability as excellent. The participants were asked about their satisfaction while relying on the proposed system and the guidance provided for indoor navigation.

Similarly, the system was evaluated with Likert Scale questionnaire, which showed the overall usability of the system and yielded a high positive response from the overall results indicate the significance of the proposed method and its ease of use. The system was evaluated by a sample of participant. Changing the users may yield somehow different results.

## 6.1 Limitations and Future Work

1. In our system, the user holds the smartphone in his/her hand, which is still not easy while navigating in the environment. This issue can be resolved by integrating an AR headset.
2. The localization of the point clouds can be made automated and less time taking.
3. One limitation of our work is that it directs the users in four directions including forward, backward, left, right. It requires a structured indoor environment. The marker placement is required to be parallel to the corresponding paths. In future, we are planning to solve this issue.
4. In the future, we plan to add a point of interest (POIs) with a name showing when users reach their destination and a virtual guide with audio/text speech.
5. In the future, we can also develop applications further to offer alternative routes to the user. For instance, sometimes the shortest route may not be the most desirable, and users prefer the warmest route to the destination during weather changes. Therefore, by adding live weather details and according to that, a popup message which provides information regarding the weather condition and gives the option to choose an alternative path.
6. We analyze the results by comparing the time difference between the 2D map and AR prototype to see which navigation method would take less time to reach the destination. But in the future, we can also test indoor navigation methods to check the usability of the system, like the ease of use, to check which navigation method users would prefer to navigate indoors.

## 6.2 Final Thoughts

We proposed a new method for assisting users with indoor navigation and localization. An automated system is proposed as a solution for efficiently identifying and generating paths within a large building. When opposed to other researchers' solutions, it has very low implementation costs. The guidance module allows users to find the shortest path to their destination in a single or multi-story house. The overall navigation system proved to be an effective, accurate, and simple-to-use solution after testing it with real users and analyzing the results.

# References


1. Ajith, A., Thomas, A. M., Antony, J., & Joseph, J. (2020). Indoor Mapping Based on Augmented Reality Using Unity Engine. International Journal of Innovative Science and Research Technology., 5(5), 1547-1550. Retrieved from https://ijisrt.com/assets/upload/files/IJISRT20MAY756.pdf.
2. Azuma, R.T. A Survey of Augmented Reality. Presence Teleop. Virtual Environ. 1997, 6, 355–385, doi:10.1162/pres.1997.6.4.355.
3. Satan, “Bluetooth-based indoor navigation mobile system,” 2018 19th International Carpathian Control Conference (ICCC), Szilvasvarad, 2018, pp. 332-337.
4. H. Chabbar and M. Chami, “Indoor localization using Wi-Fi method based on a Fingerprinting Technique,” 2017 International Conference on Wireless Technologies, Embedded and Intelligent Systems (WITS), Fez, 2017, pp. 1-5.
5. Mautz, R. (2009). “Overview of current indoor positioning systems”. In: Geodezija ir kartografija 35.1, pp. 18–22.
6. Dardari, D., P. Closas, and P. M. Djuri´c (2015). “Indoor tracking: Theory, methods, and technologies”. In: IEEE Transactions on Vehicular Technology 64.4, pp. 1263–1278.
7. Filonenko, V., C. Cullen, and J. D. Carswell (2013). “Indoor positioning for smartphones using asynchronous ultrasound trilateration”. In: ISPRS International Journal of Geo-Information 2.3, pp. 598–620.
8. Bielsa, G. et al. (2018). “Indoor localization using commercial off-the-shelf 60 GHz access points”. In: IEEE INFOCOM 2018-IEEE Conference on Computer Communications. IEEE, pp. 2384–2392.

9. Martin, E. et al. (2010). “Precise indoor localization using smart phones”. In: Proceedings of the 18th ACM international conference on Multimedia, pp. 787–790.
10. Husen, M. N. and S. Lee (2014). “Indoor human localization with orientation using WiFi fingerprinting”. In: Proceedings of the 8th International Conference on Ubiquitous Information Management and Communication, pp. 1–6
11. Subedi, S. and J.-Y. Pyun (2017). “Practical fingerprinting localization for indoor positioning system by using beacons”. In: Journal of Sensors 2017.s
12. Kaushal, H., V. Jain, and S. Kar (2017). Free space optical communication. Vol. 1. Springer
13. Rosenfeld, A. (1988). “Computer vision: basic principles”. In: Proceedings of the IEEE 76.8, pp. 863–868.
14. Mulloni, A. et al. (2009). “Indoor positioning and navigation with camera phones”. In: IEEE Pervasive Computing 8.2, pp. 22–31
15. Fusco, G. and J. M. Coughlan (2018). “Indoor localization using computer vision and visual-inertial odometry”. In: International Conference on Computers Helping People with Special Needs. Springer, pp. 86–93.
16. März, T., & Weinmann, A. (2016). Model-based reconstruction for magnetic particle imaging in 2D and 3D. *Inverse Problems and Imaging*, *10*(4), 1087–1110. https://doi.org/10.3934/ipi.2016033
17. G. Gerstweiler, E. Vonach, and H. Kaufmann, “HyMoTrack: A Mobile AR Navigation System for Complex Indoor Environments,” Sensors, vol. 16, no. 1, p. 17, Dec. 2015.
18. T. Bailey and H. Durrant-Whyte, “Simultaneous localization and mapping (SLAM): Part II,” IEEE Robot. Autom. Mag., vol. 13, no. 3, pp. 108–117, 2006.

19. Volk, R.; Stengel, J.; Schultmann, F. Building Information Modeling (BIM) for existing buildings—Literature review and future needs. Autom. Constr. 2014, 38, 109–127. modelling
20. Patraucean, V.; Armeni, I.; Nahangi, M.; Yeung, J.; Brilakis, I.; Haas, C. State of research in automatic as-built modelling. Adv. Eng. Inform. 2015, 29, 162–171. modelling
21. Liu, L.; Zlatanova, S. Generating navigation models from existing building data. Int. Arch. Photogramm. Remote Sens. Spat. Inf. Sci. 2013, 40, 19–25. modelling
22. Oesau, S.; Lafarge, F.; Alliez, P. Indoor scene reconstruction using feature sensitive primitive extraction and graph-cut. ISPRS J. Photogramm. Remote Sens. 2014, 90, 68–82. modelling
23. Mura, C.; Mattausch, O.; Pajarola, R. Piecewise-planar Reconstruction of Multi-room Interiors with Arbitrary Wall Arrangements. Comput. Gr. Forum 2016, 35, 179–188. modelling
24. Tran, H.; Khoshelham, K.; Kealy, A.; Díaz-Vilariño, L. Shape Grammar Approach to 3D Modelling of Indoor Environments Using Point Clouds. J. Comput. Civ. Eng. 2019, 33, 14. modelling
25. Staats, B.R.; Diakité, A.A.; Voûte, R.L.; Zlatanova, S. Automatic generation of indoor navigable space using a point cloud and its scanner trajectory. ISPRS Ann. Photogramm. Remote Sens. Spat. Inf. Sci. 2017, 4, 393–400. modelling
26. Balado, J.; Díaz-Vilariño, L.; Arias, P.; González-Jorge, H. Automatic classification of urban ground elements from mobile laser scanning data. Autom. Const. 2018, 86, 226–239. modelling
27. Balado, J.; Díaz-Vilariño, L.; Arias, P.; Soilán, S. Automatic building accessibility diagnosis from point clouds. Autom. Const. 2011, 82, 103–111. modelling

28. Díaz-Vilariño, L.; Verbree, E.; Zlatanova, S.; Diakité, A. Indoor modelling from slam-based laser scanner: Door detection to envelope reconstruction. Int. Arch. Photogramm. Remote Sens. Spat. Inf. Sci. 2017, 42, 345–352. modelling
29. Nikoohemat, S.; Peter, M.; Oude Elberink, S.; Vosselman, G. Exploiting indoor mobile laser scanner trajectories for semantic interpretation of point clouds. ISPRS Ann. Photogramm. Remote Sens. Spat. Inf. Sci. 2017, 4, 355–362. modelling
30. Nikoohemat, S.; Peter, M.; Oude Elberink, S.; Vosselman, G. Semantic Interpretation of Mobile Laser Scanner Point Clouds in Indoor Scenes Using Trajectories. Remote Sens. 2018, 10, 1754. modelling
31. Guzzi, J.; Di Carlo, G. From indoor GIS maps to path planning for autonomous wheelchairs. In Proceedings of the IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS), Daejeon, Korea, 9–14 October 2016.
32. De Berg, M.; Van Kreveld, M.; Overmars, M.; Schwarzkopf, O.C. Computational Geometry, 2nd ed.
33. Goetz, M.; Zipf, A. Formal definition of a user adaptive and length-optimal routing graph for complex indoor environments. Geo-Spat. Inf. Sci. 2011, 14, 119–128. modelling
34. Wang, Z.; Zlatanova, S.; Van Oosterom, P. Path Planning for First Responders in the Presence of Moving Obstacles With Uncertain Boundaries. IEEE Trans. Intell. Transp. Syst. 2017, 18, 2163–2173. modelling
35. Liu, L.; Xu, W.; Penard, W.; Zlatanova, S. Leveraging Spatial Model To Improve Indoor Tracking. Int. Arch. Photogramm. Remote Sens. Spat. Inf. Sci.-ISPRS Arch. 2015, 40, 75–80. modelling

36. Rodenberg, O. The Effect of A* Pathfinding characteristics on the path length and performance in an octree representation of an indoor point cloud. Master's Thesis, Technical University of Delft, Delft, The Netherlands, 2016.

37. Li, F.; Zlatanova, S.; Koopman, M.; Bai, X.; Diakité, A. Universal path planning for an indoor drone. Autom. Constr. 2018, 95, 275–283. Modelling

38. Möller, A., Kranz, M., Huitl, R., Diewald, S., & Roalter, L. (2012). A mobile indoor navigation system interface adapted to vision-based localization. In 11th International Conference on Mobile and Ubiquitous Multimedia (pp. 1–10). Ulm: ACM. https://doi.org/10.1145/2406367.2406372

39. Mulloni, A., Wagner, D., Schmalstieg, D., & Barakonyi, I. (2009). Indoor positioning and navigation with camera phones. IEEE Pervasive Computing, 8(2), 22–31. https://doi.org/10.1109/MPRV. 2009.30

40. Klopschitz, M., Schall, G., Schmalstieg, D., & Reitmayr, G. (2010). Visual tracking for augmented reality. In 2010 International Conference on Indoor Positioning and Indoor Navigation (IPIN) (pp. 1–4). Zürich: IEEE. https://doi.org/10.1109/IPIN.2010.5648274

41. Mautz, R. & Tilch, S. (2011). Survey of optical indoor positioning systems. In 2011 International Conference on Indoor Positioning and Indoor Navigation (IPIN) (pp. 1–7). Guimarães: IEEE. https://doi.org/10.1109/IPIN.2011.6071925

42. Klopschitz, M., Schall, G., Schmalstieg, D., & Reitmayr, G. (2010). Visual tracking for augmented reality. In 2010 International Conference on Indoor Positioning and Indoor Navigation (IPIN) (pp. 1–4). Zürich: IEEE. https://doi.org/10.1109/IPIN.2010.5648274

43. Mautz, R. (2012). Indoor positioning technologies (Habilitation thesis, ETH Zurich).

44. Chang, Y.-j., Tsai, S.-k., Chang, Y.-s., & Wang, T.-y. (2007). A novel wayfinding system based on geo-coded QR codes for individuals with cognitive impairments. In

9th International ACM SIGACCESS Conference on Computers and Accessibility (pp. 231–232). Tempe: ACM. https://doi.org/10.1145/1296843.1296887

45. Mulloni, A., Wagner, D., Schmalstieg, D., & Barakonyi, I. (2009). Indoor positioning and navigation with camera phones. IEEE Pervasive Computing, 8(2), 22–31. https://doi.org/10.1109/MPRV. 2009.30
46. Raj, R. C., Tolety, S. B., & Immaculate, C. (2013). QR code-based navigation system for closed building using smart phones. In 2013 International Mutli-Conference on Automation, Computing, Communication, Control and Compressed Sensing (iMac4s) (pp. 641–644). Kottayam: IEEE. https://doi.org/10.1109/iMac4s.2013.6526488
47. Barberis, C., Bottino, A., Malnati, G., & Montuschi, P. (2014). Experiencing indoor navigation on mobile devices. IT Professional, 16(1), 50–57. https://doi.org/10.1109/MITP.2013.54
48. Chen, C.-c., Chang, C.-y., & Li, Y.-n. (2013). Range-free localization scheme in wireless sensor networks based on bilateration. International Journal of Distributed Sensor Networks, 2013(Article ID 620248), 1–10. https://doi.org/10.1155/2013/620248
49. Amundson, I. & Koutsoukos, X. D. (2009). A survey on localization for mobile wireless sensor networks. In R. Fuller & X. D. Koutsoukos (Eds.), Mobile entity localization and tracking in gps less environments (pp. 235–254). Berlin Heidelberg: Springer. https://doi.org/10.1007/978- 3-642-04385-7_16
50. Nuaimi, K. A. & Kamel, H. (2011). A survey of indoor positioning systems and algorithms. In International Conference on Innovations in Information Technology (pp. 185–190). Abu Dhabi: IEEE. https://doi.org/10.1109/INNOVATIONS.2011.5893813

51. Gu, Y., Lo, A., & Niemegeers, I. (2009). A survey of indoor positioning systems for wireless personal networks. IEEE Communications Surveys & Tutorials, 11(1), 13–32. https://doi.org/10.1109/ SURV.2009.090103

52. Liu, H., Darabi, H., Banerjee, P., & Liu, J. (2007). Survey of wireless indoor positioning techniques and systems. IEEE Transactions on Systems, Man, and Cybernetics, Part C: Applications and Reviews, 37(6), 1067–1080. https://doi.org/10.1109/TSMCC.2007.905750

53. Fallah, N., Apostolopoulos, I., Bekris, K., & Folmer, E. (2013). Indoor human navigation systems: A survey. Interacting with Computers, 25(1), 21–33. https://doi.org/10.1093/iwc/iws010

54. Hauschildt, D. & Kirchhof, N. (2010). Advances in thermal infrared localization: Challenges and solutions. In 2010 International Conference on Indoor Positioning and Indoor Navigation (IPIN) (pp. 1–8). Zürich: IEEE. https://doi.org/10.1109/IPIN.2010.5647415

55. De-Angelis, G., Pasku, V., De-Angelis, A., Dionigi, M., Mongiardo, M., Moschitta, A., & Carbone, P. (2015). An Indoor AC Magnetic Positioning System. IEEE Transactions on Instrumentation and Measurement, 64(5), 1275–1283. https://doi.org/10.1109/TIM.2014.2381353

56. Holm, S. (2012). Ultrasound positioning based on time-of-flight and signal strength. In 2012 Interna tional Conference on Indoor Positioning and Indoor Navigation (IPIN) (pp. 1–6). Sydney: IEEE. https://doi.org/10.1109/IPIN.2012.6418728

57. Medina, C., Segura, J. C., & De la Torre, Á. (2013). Ultrasound indoor positioning system based on a low-power wireless sensor network providing sub-centimeter accuracy. Sensors, 13(3), 3501–3526. https://doi.org/10.3390/s130303501

58. Mandal, A., Lopes, C. V., Givargis, T., Haghighat, A., Jurdak, R., & Baldi, P. (2005). Beep: 3D indoor positioning using audible sound. In Second IEEE Consumer Communications and Networking Conference (pp. 348–353). Las Vegas: IEEE. https://doi.org/10.1109/CCNC.2005.1405195

59. Höflinger, F., Zhang, R., Hoppe, J., Bannoura, A., Reindl, L. M., Wendeberg, J., . . . Schindelhauer, C. (2012). Acoustic self-calibrating system for indoor smartphone tracking (ASSIST). In 2012 International Conference on Indoor Positioning and Indoor Navigation (IPIN) (pp. 1–9). Sydney: IEEE. https://doi.org/10.1109/IPIN.2012.6418877

60. Rishabh, I., Kimber, D., & Adcock, J. (2012). Indoor localization using controlled ambient sounds. In 2012 International Conference on Indoor Positioning and Indoor Navigation (IPIN) (pp. 1–10). Sydney: IEEE. https://doi.org/10.1109/IPIN.2012.6418905

61. Sertatil, C., Altinkaya, M. A., & Raoof, K. (2012). A novel acoustic indoor localization system employing CDMA. Digital Signal Processing: A Review Journal, 22(3), 506–517. https://doi. org/10.1016/j.dsp.2011.12.001

62. Raab, F. H., Blood, E. B., Steiner, T. O., & Jones, H. R. (1979). Magnetic position and orientation tracking system. IEEE Transactions on Aerospace and Electronic Systems, AES-15(5), 709–718. https://doi.org/10.1109/TAES.1979.308860

63. Li, B., Gallagher, T., Dempster, A. G., & Rizos, C. (2012). How feasible is the use of magnetic field alone for indoor positioning? In 2012 International Conference on Indoor Positioning and Indoor Navigation (IPIN) (pp. 1–9). Sydney: IEEE. https://doi.org/10.1109/IPIN.2012.6418880

64. Sakpere, W. E. & Adeyeye, M. (2015). Can near field communication solve the limitations in mo bile indoor navigation? In I. Lee (Ed.), RFID technology integration

for business performance improvement (Chap. 3, pp. 52–79). Hershey: IGI Global. https://doi.org/10.4018/978-1- 4666-6308-4.ch003

65. Paperno, E., Sasada, I., & Leonovich, E. (2001). A new method for magnetic position and orientation tracking. IEEE Transactions on Magnetics, 37(4), 1938–1940. https://doi.org/10.1109/20. 951014.

66. Rajagopal, S., Roberts, R. D., & Lim, S. K. (2012). IEEE 802.15.7 visible light communication: Modulation schemes and dimming support. IEEE Communications Magazine, 50(3), 72–82. https://doi.org/10.1109/MCOM.2012.6163585
67. Ndjiongue, A. R., Ferreira, H. C., & Ngatched, T. M. N. (2015). Visible light communications (VLC) technology. John Wiley & Sons, Inc. https://doi.org/10.1002/047134608X.W8267
68. Jovicic, A., Li, J., & Richardson, T. (2013). Visible light communication: Opportunities, challenges and the path to market. IEEE Communications Magazine, 51(12), 26–32. https://doi.org/10. 1109/MCOM.2013.6685754
69. Hassan, N. U., Naeem, A., Pasha, M. A., Jadoon, T., & Yuen, C. (2015). Indoor positioning using visible LED lights: A survey. ACM Computing Surveys (CSUR), 48(2), 20:1–20:32. https: //doi.org/10.1145/2835376
70. Gozick, B., Subbu, K. P., Dantu, R., & Maeshiro, T. (2011). Magnetic maps for indoor navigation. IEEE Transactions on Instrumentation and Measurement, 60(12), 3883–3891. https://doi.org/10. 1109/TIM.2011.2147690
71. Farid, Z., Nordin, R., & Ismail, M. (2013). Recent advances in wireless indoor localization techniques and system. Journal of Computer Networks and Communications, 2013(Article ID 185138), 1–12. https://doi.org/10.1155/2013/185138

72. Deak, G., Curran, K., & Condell, J. (2012). A survey of active and passive indoor localisation systems. Computer Communications, 35(16), 1939–1954. https://doi.org/10.1016/j.comcom.2012. 06.004

73. X. He, Y. Wang and Y. Cao, "Researching on AI path-finding algorithm in the game development," 2012 International Symposium on Instrumentation & Measurement, Sensor Network and Automation (IMSNA), Sanya, 2012, pp. 484-486.

74. B. H. Thomas and C. Sandor, "What Wearable Augmented Reality Can Do for You," in IEEE Pervasive Computing, vol. 8, no. 2, pp. 8-11, April-June 2009.

75. D. Wenge and B. Nan, "Research of the correction scheme based on GPS coordinate transformation model," 2011 IEEE 3rd International Conference on Communication Software and Networks, Xi'an, 2011, pp. 356-358.

76. K. Azhar, F. Murtaza, M. H. Yousaf and H. A. Habib, "Computer vision-based detection and localization of potholes in asphalt pavement images," 2016 IEEE Canadian Conference on Electrical and Computer Engineering (CCECE), Vancouver, BC, 2016, pp. 1-5.

77. C. A. L. Waechter, D. Pustka and G. J. Klinker, "Vision based people tracking for ubiquitous Augmented Reality applications," 2009 8th IEEE International Symposium on Mixed and Augmented Reality, Orlando, FL, 2009, pp. 221-2